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Marcos Rodrigues Mimbrero

Review and new methodological approaches in human-caused wildfire modeling and ecological vulnerability: risk modeling at mainland Spain

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Director: Juan de la Riva Fernández
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This thesis has been prepared in form of compendium of publications. The PhD student, Marcos Rodrigues, is listed as first author and responsible for each and every one of the articles. The works that constitute the body of the thesis, its impact factor and detail of the tasks performed by each of the authors in each are as follows:

Rodrigues M, San Miguel J, Oliveira S, Moreira F, Camia A (2013) An insight into Spatial-Temporal Trends of Fire Ignitions and Burned Areas in the European Mediterranean Countries. ***Journal of Earth Science and Engineering*** 3:497-505.

JCR Impact factor: NA

In this work, the PhD student, Marcos Rodrigues Mimbrero, is responsible for most of the work, having carried out the statistical and spatial analysis, and being the main responsible for writing contents, discussion and conclusions. Dr. Jesus San-Miguel is listed as coauthor as responsible the research where this research was conducted. Dr. Sandra Oliveira has helped in collecting and organizing the information. Doctors Francisco Moreira and Andrea Camia have collaborated in reviewing the results.

Rodrigues M, de la Riva J, Fotheringham S (2014) Modeling the spatial variation of the explanatory factors of human-caused wildfires in Spain using geographically weighted logistic regression. ***Applied Geography*** 48:52-63. doi:10.1016/j.apgeog.2014.01.011

JCR Impact factor: 2.650 (Q1, "Geography").

In this work, the PhD student, Marcos Rodrigues Mimbrero, is responsible for most of the work, having carried out the statistical and spatial analysis, and being the main responsible for writing contents, discussion and conclusions. Dr. Juan de la Riva appears as coauthor in the role of PhD director, also collaborating on reviewing the results. Dr. Stewart Fotheringham is listed as coauthor as responsible the research where this research was conducted.

Rodrigues M and de la Riva J (2014) An insight into machine-learning algorithms to model human-caused wildfire occurrence. ***Environmental Modelling & Software*** 57:192-201. doi:10.1016/j.envsoft.2014.03.003

JCR Impact factor: 4.538 (Q1, "Ecological modeling").

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Rodrigues M, Ibarra P, Echeverría M, Pérez-Cabello F, de la Riva J (2014) A method for regional scale assessment of vegetation recovery time after high severity wildfires: case study of Spain. ***Progress in Physical Geography*** 38, 556-575. doi: 10.1177/0309133314542956.

JCR Impact factor: 3.885 (Q1, "Geography, Physical").

In this work, the PhD student, Marcos Rodrigues Mimbrero, is responsible for most of the work, having carried out the statistical and spatial analysis, and being the main responsible for writing contents, discussion and conclusions. Dr. Paloma Ibarra has worked on the characterization of plant species also helping in the literature review in this topic. Dr. Maite Echeverria has participated in developing the method for the assessment of post-fire erosion. Dr. Fernando Pérez-Cabello has provided part of the information for the development of the validation process as well as its usage. Dr. Juan de la Riva appears as coauthor in the role of PhD director, also collaborating on reviewing the results.

La presente tesis doctoral se ha elaborado siguiendo la modalidad de compendio de publicaciones. El doctorando, Marcos Rodrigues, figura como primer autor y responsable de todos y cada uno de los artículos. A continuación se detallan los trabajos que constituyen el cuerpo de la tesis, su factor de impacto y el detalle de las tareas realizadas por cada uno de los autores en cada uno de ellos:

Rodrigues M, San Miguel J, Oliveira S, Moreira F, Camia A (2013) An insight into Spatial-Temporal Trends of Fire Ignitions and Burned Areas in the European Mediterranean Countries. ***Journal of Earth Science and Engineering*** 3:497-505.

Factor de impacto JCR: NA

En este trabajo el doctorando, Marcos Rodrigues Mimbrero, ha realizado el grueso de trabajo, desarrollando la mayor parte del análisis estadístico y espacial, siendo el responsable último de la redacción de los contenidos, discusión y conclusiones. El doctor Jesús San-Miguel figura como coautor en calidad de responsable de la estancia en la que se desarrolló la investigación. La doctora Sandra Oliveira ha colaborado en las tareas de obtención y organización de la información. Los doctores Francisco Moreira y Andrea Camia han colaborado en la revisión de los resultados.

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Abstract

Over the last decades, authorities responsible on forest fire have encouraged research on fire triggering factors, recognizing this as a critical point to achieve a greater understanding of fire occurrence patterns and improve preventive measures. There is therefore a need to improve and update the methodological approaches for modeling forest fires, taking into account not only innovative algorithms, but also improving and/or overcoming classical regression methods. On the other hand it is also essential to encourage the assessment of potential damage on natural ecosystems, promoting the conservation of its economic, environmental, cultural and aesthetic assets they provide to society. The main objective of this PhD thesis is to explore new methods for modeling human causality in forest fires and adverse effects on the plant communities potentially affected.

Human causality modeling was carried out from machine learning methods and geographically weighted regression techniques. These procedures allow the adjustment spatially explicit probability models of occurrence and, secondly, the study of the spatial variability of wildfire explanatory factors.

The estimation of the vulnerability of vegetation to fire was carried out using a quantitative approach to overcome current methods, which, while they may be useful in some areas of land management, are inadequate for other types of analysis, such as estimating economic losses induced by interrupting ecosystem services (e.g., wood, hunting, and gathering mushrooms). To address the vulnerability a method based on evaluating the recovery time of plant communities after the fire using a GIS map algebra approach is proposed.

The results suggest that the use of machine learning methods (specifically the Random Forest algorithm) represents a substantial improvement over traditional methods of regression, although it appears that there is some uncertainty in the models, primarily related to the quality of ignition. Furthermore, the application of GWR models has revealed the existence of a high spatial heterogeneity in the relationship and explanatory power of the factors related to the occurrence of anthropogenic fires. Moreover, the application of the proposed model for the quantitative estimation of ecological vulnerability suggests that the responsiveness of vegetation is closely related to the reproductive strategy of the fire-affected species.

Resumen

En las últimas décadas, las autoridades en materia de incendios han fomentado la investigación acerca de los factores desencadenantes del fuego, parámetro decisivo para lograr un entendimiento mayor de los patrones de la ocurrencia de incendios y mejorar las medidas preventivas. Existe por tanto una necesidad de mejorar y actualizar los enfoques metodológicos para el modelado de incendios forestales, teniendo en cuenta no sólo algoritmos innovadores, sino también la mejora y/o superación de los métodos clásicos de regresión. Por otra parte, es también imprescindible fomentar la evaluación de los posibles daños potenciales en los ecosistemas naturales, promoviendo así la conservación de los servicios de valor económico, ambiental, cultural y estético que éstos proporcionan a la sociedad. El objetivo principal de esta tesis doctoral es explorar nuevos métodos para el modelado de la causalidad humana en incendios forestales así como de los efectos adversos sobre las comunidades vegetales potencialmente afectadas.

El modelado de la causalidad humana se ha realizado a partir de métodos de aprendizaje artificial y de técnicas de regresión geográficamente ponderada. Estas técnicas permiten por una parte el ajuste de modelos de probabilidad de ocurrencia espacialmente explícitos y, por otra, el estudio de la variabilidad espacial de los factores explicativos.

La estimación de la vulnerabilidad de la vegetación frente al fuego, se ha llevado a cabo utilizando un enfoque cuantitativo, que permita superar los métodos existentes, que, si bien pueden ser útiles en algunas áreas de la gestión del territorio, son inadecuados para otros tipos de análisis, tales como la estimación de las pérdidas económicas inducidas por el fuego como consecuencia de la interrupción de los servicios ambientales (por ejemplo, la madera, la caza, y la recolección de setas). Para abordar el análisis de la vulnerabilidad se propone un método basado en la estimación del tiempo de recuperación de las comunidades vegetales tras el fuego, desarrollado mediante álgebra de mapas en entorno SIG.

Los resultados indican que la utilización de métodos de aprendizaje artificial (concretamente el algoritmo Random Forest) supone una mejora sustancial respecto a los métodos clásicos de regresión, si bien parece que existe cierta incertidumbre en los modelos desarrollados, relacionada principalmente con la calidad de los datos de ocurrencia. Además, la aplicación de modelos GWR ha revelado la existencia de una elevada heterogeneidad espacial en la relación y capacidad explicativa de los factores relacionados con la ocurrencia de incendios con origen antrópico. Por otra parte, la aplicación del modelo propuesto para la estimación cuantitativa de la vulnerabilidad ecológica sugiere que la capacidad de respuesta de la vegetación se encuentra estrechamente relacionada con la estrategia reproductiva de las especies afectadas.

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CHAPTER 1. BACKGROUND AND RESEARCH DEVELOPMENT

This chapter presents the research framework, describing the study area an introducing the conceptual approaches used to conduct the research.

1.1. Fire as a disturbance hazard and landscape transformation factor

Fire is a natural factor that has shaped Earth's vegetation throughout its natural history. The control of fire by persons has extended the influence of fire beyond its ecological limits, offering human beings a powerful tool for land cleaning and soil alteration (Chuvieco, 2009). Forest fires are thus a major factor of environmental transformation in a wide variety of ecosystems, affecting forested areas and having an important share in greenhouse gas emissions (van der Werf *et al*., 2010), and vegetation dynamics (Thonicke *et al*., 2010). However, although fire was in origin a natural process –as it may be caused by natural factors such as lightning, or volcanic eruptions– nowadays fire has acquired an anthropogenic dimension being mainly controlled by human activities (Chuvieco, 2009).

Fire effects are commonly associated to fire frequency and intensity, implying loss of lives and damages on infrastructures, soil degradation, and biodiversity losses. The main trends of environmental degradation induced by fire in the medium and long term may include permanent changes in the floristic composition of the plant community, reduction of vegetation cover, biomass loss, and alteration of landscape patterns. Forest fires can also induce long-term changes in floristic and physiognomic parameters of vegetation through their impact on the physical and chemical properties and nutrient availability of soil (Vallejo *et al*., 2009; Pérez-Cabello *et al*., 2009). In addition, the loss of vegetation cover after fire increases surface erosion because the bare soil is exposed to raindrop impact and surface runoff, especially in the first months after burning (Giovannini *et al*., 2001; Inbar *et al*., 1998). On the other hand, in several developed countries, growing industrialization has led to a severe reduction of rural population and an abandonment of traditional rural practices (Martínez *et al*., 2009). This phenomenon has implied a remarkable increase of fuel accumulation, conducing to more severe and intense fires and consequently to higher impacts. In developing countries, the reverse is true, and continuous movement of the agricultural frontier threats tropical forest. Fire is used in this context as a clearing tool for land use transformation.

Noticeably, fire effects on both society and environment largely depend on fire regime (density, frequency, severity, intensity, seasonality, size, etc.). Fire is beneficial for vegetation when it is well adapted to natural conditions, but harmful when natural cycles or fire regimes are altered (Chuvieco, 2009). Recent changes in socioeconomic models and climatic patterns have significantly affected the historical fire regime (González *et al*., 2010; San-Miguel-Ayanz *et al*., 2012a), with potential damage far greater than traditionally experienced (Bowman and Boggs, 2006; Meyn *et al*., 2007;

Pausas and Vallejo, 1999). In addition there appears to be increased chances of having an especially dramatic season, similar to those that several countries suffered in the last decade as a result of extreme heat waves (Spain 2000 and 2005; Portugal 2003 and 2005; Greece 2007). This increase in wildfire frequency, with its associated risks to the environment and society (Moreno *et al*., 2011), and the potential undesired effects on environment and society calls for a better understanding of the wildfire phenomenon.

During the last decades, the Spanish forest fire authorities have encouraged the investigation of fire causes, which is decisive to better understand patterns of fire occurrence and improve fire prevention measures (Martínez *et al*., 2009). However, the 29% of the fire causes remain unidentified. According to Lovreglio *et al*. (2006), little is known about wildfire causes, which often are more diverse than what is assumed by the traditional classifications employed for statistical purposes. In face of the arising uncertainties, a better knowledge on spatial patterns of fire occurrence and their relationships with its underlying causes becomes a necessity to locate and make prevention efforts more efficient.

1.2. Study area

Forest fires have traditionally been linked to the Mediterranean climate due to the coexistence, in some months of the year, of high temperatures and low rainfall (Camia and Amatulli, 2009). The indigenous vegetation has lived with fire for millennia, and thus it is not an extraneous factor to the Mediterranean environment or, more specifically, to peninsular Spain (Pausas and Vallejo, 1999; Pyne, 2009; Wagtendonk, 2009). In Spain, the total area burned –with an annual average of over 125 000 hectares from 2000 to 2010, but almost 250 000 hectares per year from 1980 to 1989 (Schmuck, 2011)– has decreased in recent years, while the number of fires has increased –18 150 compared to 15 300 in the corresponding periods (San-Miguel-Ayanz *et al*., 2012a; Schmuck, 2011)–. The current climate change trend in the Mediterranean is provoking longer summer droughts and intensification of these droughts even out of season. Also, extreme weather events, such as periods of high temperatures, strong air dryness and very strong winds, as well as sudden storms with heavy rainfall in only few hours (an amount similar to the annual average rainfall in some areas), are becoming frequent. Thus, the chances of suffering an especially dramatic fire season (Rebetez *et al*., 2006), as in several countries in the last decade as a result of extreme heat waves (Spain, 2000 and 2005; Portugal, 2003 and 2005; Greece, 2007; Australia, 2009; Russia, 2010) appear to be increased (Camia and Amatulli, 2009; San-Miguel-Ayanz *et al*., 2012b) and are likely to occur more frequently in the coming decades (Seidl *et al*., 2011).

The Mediterranean has been identified by WWF as one of the most important regions in the world for its outstanding biodiversity features. Mediterranean forests, situated in a transitional zone between the European, African and Asian continents, are one of the planet's centres of plant diversity, with 25,000 floral species representing 10% of the world's flowering plants on just over 1.6% of the Earth's surface. They also play host to an amazing faunal diversity. But the Mediterranean forests are also under serious threat, with forest fires, in most cases deliberately set, playing a major role in their degradation and bringing about huge social, economic and environmental effects. There is a strong need to put in place an effective policy of prevention to address the root causes of this phenomenon.

The study area covers the whole of peninsular Spain excluding the Balearic and Canary Islands and the autonomous cities of Ceuta and Melilla except in the case of Chapter 5 which is developed at European level to establish an initial framework to contextualize wildfire impact in Spain within the EUMed Region. Further, the study region was restricted to wildland areas; consequently, urban areas and agricultural and inland water zones were excluded from the assessment and no data are detailed or shown on the maps.

Spain is very biophysically diverse, presenting a wide variety of climatic, topographic, and environmental conditions. This diversity also appears when discussing socioeconomic conditions, in terms of population systems and population structure, productive sector, or territory structure. The complexity of the socioeconomic conditions thus plays a determinant role, which is especially important when modeling human factors, since this complexity is transferred to the relationships between socioeconomic variables and a natural phenomenon such as wildfires, making assessment less straightforward.

1.3. Forest Fire Risk assessment Systems

1.1.1. Fire risk conceptual approaches: fire danger and vulnerability

The conceptual definition of a Forest Fire Risk assessment System (FFRS) should include the most relevant components associated with the fire process. Terminology used in fire prevention planning has a long tradition, especially in the US and Canada, but is still quite controversial, especially when comparing its terms with those used in other natural hazards (earthquakes, volcanic eruptions, floods, etc.). Following the most common terminology used by fire managers, 'fire hazard' refers to the potential fire behavior associated with the 'static' properties of fuel, regardless of the particular moisture conditions on a given day.

The term 'fire risk' refers to the 'chance of fire starting, as determined by the presence and activity of causative agents' (mainly lightning and human factors). The concept of 'fire danger' is broader and describes the 'factors affecting the inception, spread and resistance to control, and subsequent fire damage; often expressed as an index' (NWCG, 2014). Following this approach, fire danger includes various factors: weather conditions, causative agents and even potential damage, but most commonly the latter are not considered in operational fire danger assessment systems (San Miguel-Ayanz *et al*., 2003). Some authors are critical of the term 'danger', as its meaning is vague, and suggest fire hazard or fire probability be used instead (Bachmann and Allgöwer, 2001).

In other natural hazards, the term 'risk' commonly describes the convergence of the physical probability that a natural event occurs, and its potential damage to people and the environment (UNISDR, 2009). Following this approach, fire risk mapping should include the assessment of values potentially affected by fire. In fact, those values are critical to guide fire suppression efforts (a clear example is when fire occurs in the proximity of urbanized areas). Therefore, the consideration of fire vulnerability (potential effects of fire on social and ecological values) should always be part of fire risk evaluations and would help to align them with other natural hazard assessments.

Several authors have adapted this risk approach to wildland fires (Allgöwer *et al*., 2003; Bachmann and Allgöwer, 2001; Chuvieco *et al*., 2003), which implies that fire risk assessment should both include the probability that a wildfire ignites or propagates (which we will name as fire danger throughout this paper), and the expected damages caused by fire behavior (termed as fire vulnerability). Recent papers on fire risk assessment have incorporated this double evaluation to propose a comprehensive analysis of fire risk conditions (Calkin *et al*., 2010; Chuvieco *et al*., 2010; Thompson *et al*., 2011; Tutsch *et al*., 2010), but still much more research exists on fire danger than on fire vulnerability. In recent years, several methods for wildfire risk assessment have been developed using different methodological schemes, variables, and scales (Martínez-Vega, 2012). Without being exhaustive, some of the more recent efforts have included those by Amatulli *et al*. (2006), Chuvieco *et al*. (2014; 2010), Cooke *et al*. (2007), Loboda (2009), Martínez *et al*. (2011; 2009), Martinez and Koutsias (2013), Padilla and Vega-García (2011), and Romero-Calcerrada *et al*. (2010). Similar efforts have been invested in modeling fire occurrence (see Plucinsky (2011) for an exhaustive review) and, particularly, to human-caused ignition (Martínez-Fernández and Koutsias, 2011; Martínez *et al*., 2013; Martínez *et al*., 2009; Padilla and Vega-García, 2011).

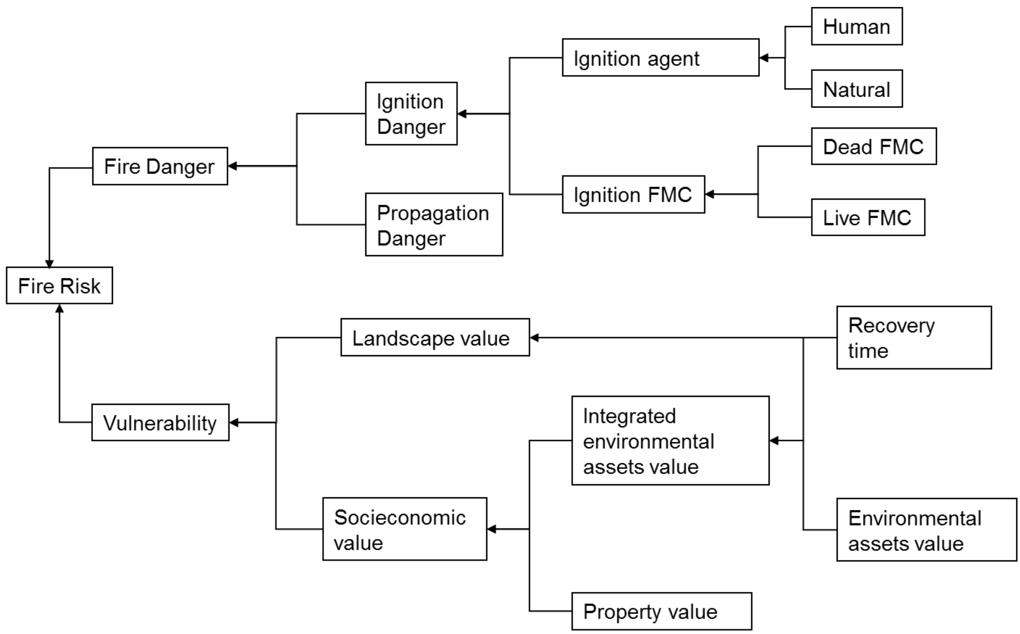

Figure 1. Framework for an integrated fire risk assessment system (Chuvieco *et al*., 2014).

The conceptual framework, in which this PhD research work has been developed in is based on Chuvieco *et al*. (2012), which considers the risk as a product of the physical probability of a fire occurs or propagates, and the potential damages that it may cause (Figure 1; see Appendix A for deeper insights). The former, fire danger, considers the probability that a fire starts as a result of any causative agent or propagates throughout space. The latter includes damages related to socio-economic and ecological values, and will be named as fire vulnerability in this document. This conceptual framework was initially proposed under the European project Spread (Allgöwer *et al*., 2003; Calkin *et al*., 2010; Chuvieco *et al*., 2003), and further refined in the Spanish projects Firemap and Fireglobe (Chuvieco *et al*., 2014; Chuvieco *et al*., 2010), funded under the CICyT calls.

1.1.2. The human component in fire risk modeling

Human beings have a great impact on fire regimes because they alter ignition frequency, fuel fragmentation and suppress fires (Guyette, 2002). The dynamics of fire regimes in southern Europe are related mainly to human factors, which are the cause of more than 95% of fires in this region (San-Miguel Ayanz and Camia, 2009). Traditional usage of fire in agricultural and cattle raising practices in the region is one of the main causes of forest fires.

Demographic changes related to the abandonment of rural areas are also related to increased fire hazard, favoring fuel accumulation due to the lack of forest management practices in the region finally leading to uncontrolled forest fires. In addition, although overall the rural population in Southern Europe has decreased, peaks of high population density in recreational wildland areas during holiday periods increased fire ignition in summer months. This is further enhanced by the expansion of urban areas into wildland areas. This effect, which is due to either the expansion of cities or the construction of secondary houses in rural areas, has led to an extended Wildland Urban Interface (WUI) in the region. The difficult fire management of the extensive WUI in Southern Europe has been the cause of catastrophic fires such as those in Portugal in 2003 or Greece in 2007.

The analysis of human factors in forest fires is widely recognized as critical for fire risk estimation (Kalabokidis *et al*., 2002; Martínez, 2004). In most countries human activities are in one way or the other, the main responsible source of fire ignition. In spite of the importance of these human aspects, little work has been devoted to this issue and the literature on this topic is scarce and mainly site-specific (Krawchuk, 2009; Le Page *et al*., 2010; Martínez *et al*., 2009), maybe because of the complexity of predicting human behavior, both in space and time. Most frequently, the studies have focused on variables related to land use or land cover-change –rural abandonment, agricultural-forest interface or urban-forest interface–, population trends, rural activities, potential conflicts that may lead to vengeances or arson –unemployment, enforcement of conservation areas, reforestation in traditional pastured areas, etc.–.

The influence of human factors on fires can be considered as both a cause and an effect. Studies pertaining to the former aspect are more abundant because human activities are the most common cause of fires –95% of Spanish fires are human-caused according to national statistics (Martínez *et al*., 2009)–. Identifying the most important factors involved in fire occurrence has been the main goal of a wide range of studies, commonly based on statistical approaches, which try to explain historical human caused fire occurrence based on a set of independent variables (Chuvieco and Justice, 2010; Martínez *et al*., 2009; Padilla and Vega-García, 2011; Syphard *et al*., 2007). The consideration of human values in fire risk assessment is more recent and only a few regional studies have identified that the main socioeconomic damages potentially caused by wildland fires are associated with lives, property and environmental services –wood products, hunting, fungi, carbon stocks, recreational, etc. (Loomis, 2004; Venn and Calkin, 2009). Previous studies in several Spanish regions (Chuvieco *et al*., 2010) demonstrated the importance of taking into account regional variation in human factors when explaining fire occurrence.

Currently, most fire risk models in use are based on physical parameters such as weather data or fuel moisture content –there is no global forest fire risk system that includes the human factors operationally, although some consider it in their components (San-Miguel Ayanz and Camia, 2009). However, over recent years, the role of human factors in fire behavior modeling has been increasing, and several models now include an anthropogenic component in their assessments (Chuvieco *et al*., 2014; Chuvieco *et al*., 2010; Loepfe *et al*., 2011).

1.1.3. The ecological vulnerability

Assessment of vegetation response after fire can support governments' forestry policies, forest service activities, and fire-risk modeling. This point is particularly acute because the lack of spatial data on this subject has to some extent hindered natural resources management agencies from identifying priority areas for adaptation measures (Brooks *et al*., 2006; Hannah *et al*., 2002)Brooks *et al*., 2006; Hannah *et al*., 2002). This hindrance is especially true in Mediterranean-type ecosystems where fire is considered the main natural disturbance, exerting a decisive influence on the structure and dynamics of plant and animal communities (Arianoutsou *et al*., 2011; Bajocco *et al*., 2011; Di Castri and Mooney, 1973; Gill *et al*., 1981; Naveh, 1975; Trabaud and Lepart, 1980)

The term vulnerability has many different definitions. Based on the one proposed by IPCC, it is understood as the extent to which a system is susceptible to, and unable to cope with, adverse effects of any driver of change or hazard (fire, in this case). Thus, ecological vulnerability to fire can be defined as the susceptibility of the ecosystem to be changed as a consequence of fire. Environmental features, as well as vegetation structure are key factors to estimate that vulnerability (Duguy *et al*., 2012). Although vulnerability aspects (relating to the potential damage of a given hazard) are frequently considered in assessment systems for most natural hazards (Bachmann and Allgöwer, 2001), they are not generally included in the operational fire danger indices used in European Mediterranean countries, which mostly rely on meteorological indices (Chuvieco *et al*., 2010). Ecological vulnerability can be used at several hierarchical levels, but is applied here as synonym for ecosystem vulnerability, defined as the inability of an ecosystem (biological community and habitat combined) to restore by itself, recovering its pre-impact (pre-fire) status.

Ideal ecosystem vulnerability assessments should involve the abiotic environment, the system’s different organization levels and several temporal and spatial scales (Ippolito *et al*., 2010). A comprehensive vulnerability analysis is, thus, unrealistic and, in practice, 'reduced' assessments are conducted (Turner *et al*., 2003). Effects of fire on soils and post-fire vegetation dynamics have been studied in Mediterranean basin ecosystems (Duguy *et al*., 2007; Duguy and Vallejo, 2008; Kazanis and Arianoutsou, 2004). In addition, several methodologies for assessing vegetation response to forest fires in Mediterranean-type ecosystems have already been designed. Bisson *et al*. (2008) presented an index of plant community resilience to fire. Arianoutsou *et al*. (2011) evaluated the post-fire resilience of *Pinus halepensis* in Cape Sounion National Park, Greece, using GIS and multi-criteria analysis. De la Riva *et al*. (2008), Alloza *et al*. (2006), and Duguy *et al*. (2012) produced a qualitative index of ecological vulnerability to forest fire in Mediterranean environments. In any case, these methods provide qualitative results; however, while they may be useful in some areas for territorial management, they are inadequate for other kinds of analyses such as quantitative assessment of fire-induced economic losses due to interruption of environmental services (e.g. timber, hunting, and mushroom gathering). For these, it is essential to know the period during which that service was lost (Román *et al*. 2013, see Appendix B).

CHAPTER 2. OBJECTIVES AND STRUCTURE

This chapter summarizes the objectives of the thesis and puts them in connection with the publications and supplementary materials that compose the thesis.

The main objective of this thesis is to explore new methods for modeling anthropogenic causality in forest fires and fire effects on burnt plant communities. Achieving this objective requires taking into account several components or dimensions relating the wildfire phenomena and spatial modeling, which every fire risk approach or method have to address properly.

On the one hand, fire is a spatial hazard and consequently it depends on parameters that have a spatial explicit basis. For instance, fire ignition drivers or explanatory factors are spatially distributed parameters that could show spatially varying relationships with forest fires, also being scale-dependent. These issues should be adequately considered when exploring new approaches, thus analyzing in depth their ability to properly reflect the spatial behavior of wildfires.

Fire is not only a spatial phenomenon but also has a strong temporal component. Forest fires are a dynamic hazard which shows high temporal variability both inter- and intra-annual (fire regimes, seasonality, trends…). The temporal scale or dimension of wildfires is an essential component and therefore it has to be accurately incorporated into any fire risk assessment. For example, new approaches should deal with temporal evolution of fires (trend analysis) or identify its structural components (historic models).

A third component of wildfires and in fact always present when dealing with environmental processes and inherent to statistical models, is uncertainty. Uncertainty is basically a lack of information that propagates through models and therefore influences the results. It is present at any stage of analysis, staring from inputs, being present in models and methods, and finally in the results. From a scientific perspective, improving decision quality in natural resource management begins with uncertainty management. Consequently, new methodological approaches are unreliable unless they are self-critical and thus address the uncertainty of its outputs.

Finally, although not a specific component of forest fires modeling but a requirement for statistical and spatial hazard modeling, developing and exploring new methods entails appropriate tools for its proper development. In this sense, this thesis has deeply explored the use of several tools, combining traditional GIS approaches with statistical and programming languages, either open source or proprietary. Developing adequate methods usually require the design and implementation of complex workflows to which scripting tools are a necessity. This is even truer when working at wide scales or with a huge amount of information as is the case.

All these four components or requirements have been addressed in this work thorough the different publications that compose the PhD thesis. Each of the documents covers in higher or lesser degree one or more of the requirements, allowing not only achieving the main objective but doing it guarantying its consistency and rigor.

The global objective has been broke down into several specific sub-objectives summarized as follows. These objectives, and consequently this PhD research work, have been addressed as a compendium of publications. Table 1 presents the relationship between specific objectives and publications.

i. Provide insights into the temporal evolution of the wildfire phenomenon.
ii. Review existing methodological approaches in the field of human factors modeling of ignition and ecological vulnerability.
iii. Explore the applicability of new regression methods for modeling of human causality.
iv. Estimate the spatial variation of the explanatory factors of human causality.
v. Analyze the reliability of the original data of fire occurrence and potential associated uncertainty.
vi. Estimate the ecological vulnerability of plant communities affected by fire.

The contents of the PhD document are structured as follows. Chapter 1 has introduced and contextualized the conceptual framework of the research work. Chapter 3 summarizes the material used to develop the research, extending the contents that are already included in the publications and describing them more in depth in order to enhance the comprehension of the proposed methods. Chapter 4 presents and extends the methods and techniques employed to develop the research. Jointly with chapter 3, it aims to significantly improve the comprehension of the proposed methods. Chapters 5 to 8 present the original version of the accepted and published papers. Finally, a summary of the main findings is presented in chapter 9.

Additionally, a section with supplementary materials is also included. This section introduces additional publications whose I have coauthored and are strongly related with the objectives of my PhD. These publications have been developed as a result of the research conducted in the framework of the FIREGLOBE project (CGL2008-01083/CLI) –*Analysis of fire risk scenarios at the national and global scales*–, and the research stays made during the FPI grant period (ref. BES-2009-023728).

- Appendix A introduces the work *Integrating geospatial information into fire risk assessment* which summarizes the main outputs from project FIREGLOBE as well as contextualizes the framework of research.

Table 1. Summary of PhD's objectives and its contributing papers and/or communications

Objective	Publication
i. Provide insights into the temporal evolution of the wildfire phenomenon.	***Rodrigues M**, San Miguel J, Oliveira S, Moreira F, Camia A. (2013) An insight into Spatial-Temporal Trends of Fire Ignitions and Burned Areas in the European Mediterranean Countries. Journal of Earth Science and Engineering 3:497-505.*
ii. Review existing methodological approaches in the field of human factors modeling of ignition and ecological vulnerability.	***Rodrigues M**, de la Riva J, Fotheringham S. (2014) Modeling the spatial variation of the explanatory factors of human-caused wildfires in Spain using geographically weighted logistic regression. Applied Geography 48:52-63. doi:10.1016/j.apgeog.2014.01.011* ***Rodrigues M** and de la Riva J. (2014) An insight into machine-learning algorithms to model human-caused wildfire occurrence. Environmental Modelling & Software, 57:192.201. doi:10.1016/j.envsoft.2014.03.003* ***Rodrigues M**, Ibarra P, Echeverría M, Pérez-Cabello F, de la Riva J. (2014) A method for regional scale assessment of vegetation recovery time after high severity wildfires: case study of Spain. Progress in Physical Geography 38, 556-575. doi: 10.1177/0309133314542956.*
iii. Explore the applicability of new regression methods for modeling of human causality.	***Rodrigues M**, de la Riva J, Fotheringham S. (2014) Modeling the spatial variation of the explanatory factors of human-caused wildfires in Spain using geographically weighted logistic regression. Applied Geography 48:52-63. doi:10.1016/j.apgeog.2014.01.011* ***Rodrigues M** and de la Riva J. (2014) An insight into machine-learning algorithms to model human-caused wildfire occurrence. Environmental Modelling & Software, 57:192.201. doi:10.1016/j.envsoft.2014.03.003*
iv. Estimate the spatial variation of the explanatory factors of human causality.	***Rodrigues M**, de la Riva J, Fotheringham S. (2014) Modeling the spatial variation of the explanatory factors of human-caused wildfires in Spain using geographically weighted logistic regression. Applied Geography 48:52-63. doi:10.1016/j.apgeog.2014.01.011*
v. Analyze the reliability of the original data of fire occurrence and potential associated uncertainty.	***Rodrigues M** and de la Riva J (2014) Assessing the effect on fire risk modeling of the uncertainty in the location and cause of forest fires. In Viegas DX (ed.) Advances in Forest Fire Research. Coimbra, Imprensa da Universidade de Coimbra, 1061-1072. http://dx.doi.org/10.14195/978-989-26-0884-6_116.*
vi. Estimate the ecological vulnerability of plant communities affected by fire.	***Rodrigues M**, Ibarra P, Echeverría M, Pérez-Cabello F, de la Riva J. (2014) A method for regional scale assessment of vegetation recovery time after high severity wildfires: case study of Spain. Progress in Physical Geography 38, 556-575. doi: 10.1177/0309133314542956.*

- Appendix B, *Methodological approach to assess the socio-economic vulnerability to wildfires*, presents an application example of the proposed method for quantitative assessment of ecological vulnerability, being an input to calculate the economic value of fire-affected assets.
- Appendix C, *Land Cover Change and Fire Regime in the European Mediterranean Region*, extends the results for fire trends in number of fires and burnt area size.
- Finally, appendix D and E introduce the first steps of the methods to estimate the spatial variation of the explanatory factors of human causality and the ecological vulnerability of plant communities affected by fire.

CHAPTER 3. MATERIALS

This chapter describes in deep detail the data employed to conduct this PhD research work. As noticeable, the research work has been developed using different spatial scales. Although most of the analyses have been carried out at national (Spain) level, some parts refer to the European level. Accordingly, section 3.1 presents data at European scale while in sections 3.2 and 3.3 data at national is described. On the other hand, this work follows a double-sided approach to deal with fire risk (fire danger and vulnerability to fire); therefore data on fire occurrence is firstly presented (sections 3.1 and 3.2) later introducing the materials utilized to develop the vulnerability assessment.

3.1. European Forest Fire Information System

Data on number fire events and burned area were retrieved from the EFFIS Database. European countries have collected information on forest fires since 1970s. However, the lack of harmonized information at the European level has prevented a holistic approach for forest fire prevention in the Region. The European Forest Fire Information System (EFFIS, Appendix C) has been developed jointly by the European Commission services (Directorate General Environment and the Joint Research Centre) and the relevant fires services in the countries (forest fires and civil protection services) in response to the needs of European bodies such as the Monitoring and Information Centre of Civil Protection, the European Commission Services and the European Parliament (San-Miguel-Ayanz *et al*., 2013). EFFIS is a comprehensive system covering the full cycle of forest fire management, from forest fire prevention and preparedness to post-fire damage analysis. The system provides information to over 37 countries in the European and Mediterranean regions, and receives detailed information of forest fire events from 25 countries in the European and Mediterranean regions. It supports forest fire prevention and forest fire fighting in Europe through the provision of timely and reliable information on forest fires (San-Miguel-Ayanz *et al*., 2012b).

The European Fire Database is the largest repository of information on individual fire events in Europe and an EFFIS' core component. It is the end product of a long collaboration between European countries and the European Commission on forest fires.

Since 1989 several regulations have supported the creation of forest fire information systems in the countries to monitor and evaluate the effectiveness of the measures taken at the European level. To this end the countries had to make available to the EC a minimum common set of data on forest fires. Thus a first fire database was established with information on forest fires, their size and causes. The systematic collection of a core set of data on each fire event started covering at that time six Member States of the Union: Germany, Portugal, Spain, France, Italy and Greece.

Since 2000, the forest fire data provided each year by individual EU Member States and other European countries have been checked, stored and managed by JRC within EFFIS. The database is now known as the European Fire Database, and the number of Member States and other participating European countries that contribute to it has been gradually increasing.

Today the database reflects the efforts of the 22 contributing countries that have been regularly supplying fire data: Bulgaria, Croatia, Cyprus, Czech, Estonia, Finland, France, Germany, Greece, Hungary, Italy, Latvia, Lithuania, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, Sweden, Switzerland

and Turkey, and contains over 2 million individual wildfire event records, of which about 1.66 million are classified as forest fires.

Each country has its own internal rules of reporting on individual fire events. Some store very detailed information and have complex databases for this purpose; others record only minimal and basic information. The European Fire Database therefore contains a number of commonly gathered characteristics of each fire, all of which can be supplied by all countries. The four main types of information collected are: time of fire, location of fire, size of fire, and cause of fire.

Time of fire

“Date and time of first alert” reflect the local date and time at which the official forest fire protection services were informed of the outbreak of the fire. The “Date and time of first intervention” are the local date and time on which the first fire-fighting units arrived on the scene of the forest fire. And, the “Date and time of fire extinction” are the local date and time on which the fire was completely extinguished (i.e. when the last fire-fighting units left the scene of the forest fire).

Location of fire

Wildland fires in Europe are traditionally geo-located by recording the administrative unit where they started. Two different administrative levels are requested to be specified in order to allow the maximum detail to be recorded for each fire event in the country.

A first administrative level is the province. The Nomenclature of Territorial Units for Statistics (NUTS) is a breakdown of territorial units established by the European Office for Statistics (EuroStat) for the production of regional statistics for the European Union. NUTS-3 level corresponds in most EU countries to the administrative level of provinces. The country provincial code and NUTS-3 code are requested. A second administrative level of information requested is that of the commune, corresponding to the Eurostat NUTS-5 level.

This level is much more detailed than the province and is requested also in the Country nomenclature to facilitate the correct attribution of codes and the cross checking of codes with names.

With the widespread use of GPS devices, the location of the ignition point given as geographical coordinates (latitude, longitude) is becoming more widely applied on a routine basis in many countries. When the coordinates provided are projected, the projection parameters are also requested. The geographical coordinates do not replace the specification of the administrative units.

Size of fire

Fire size is broken down into burnt land cover categories whose definition can be found in the Forest Focus Regulation§, which is compliant with FAO definitions. Where possible, the burnt area is subdivided into the 4 land cover categories “Forest”, “Other Wooded Land”, “Other Non-wooded Natural land” and “Agricultural and Other Artificial land.” If this is not possible a hybrid category may be used.

The category “agriculture and other artificial land” should be excluded in the reported burnt area statistics. It was introduced to enable its separation from the other categories to produce comparable statistics. Thus, since a fire may cover more than one type of land, the reported “total area burnt” is calculated as the sum of the burnt areas of forest, other wooded land and other non-wooded natural land. The burnt area of agricultural and other artificial land burned is not included in the numbers reflecting the burnt area.

Cause of fire

The 4 EU categories for the presumed cause are the following: 1-Unknown; 2-Natural cause (e.g. lightening, volcano); 3-Accidental cause or negligence, meaning connection to a human activity but without any intention of causing the fire (e.g. accidents caused by power lines, railways, works, bonfires, etc.); and 4-Deliberate cause or arson.

Since the currently available information on fire causes in individual countries is much more detailed than simply the 4 classes given above, cause categories following the scheme adopted by the country are also requested in addition to the 4 EU cause codes, together with a full list of local cause codes and descriptions. Based on this, a new scheme to be eventually adopted as a common fire causes classification system in Europe has been proposed (San-Miguel-Ayanz, 2012).

3.2. Fire history data in Spain: the EGIF database

In Spain, historic fire events are recorded in the General Statistics of Wildfires database (EGIF). The EGIF database is one of the oldest ‘complete’ wildfire databases in Europe, beginning in 1968 (Vélez, 2001), though its data is not considered as completely reliable until 1988 (Martínez *et al*., 2009). The database is compiled by the Ministry responsible for forest management, currently the Ministry of Environment, Rural and Marine affairs (MARM) using forest fire reports of the autonomous regions (Moreno *et al*., 2011).

Throughout his nearly forty years of existence, the form for data collection has experienced successive modifications to adapt to changes in information technology both hardware and software, the evolution of the phenomenon of forest fires, the equipment used for extinction and the changes in administrative structure and organization of the Spanish State. All these changes have enriched the number of fire data contained on the form.

EGIF is a shared database among the Autonomous Communities. Since 1990 the definition of the form and the computer application for data recording and data mining has been agreed with the autonomous responsible, guarantying that a single form and a single software application for recording and exploitation of data wildfires exists all over the State. However, a certain degree of discrepancy still exists in data collection, and information in the database differs from one region to another.

The current wildfire form includes 216 data fields for each wildfire event. Fire information is divided in two sub-forms: (i) general information of the fire and; (ii) forest specific information. In turn, each fire event is codified using a ten digit code. The first four corresponds to the year, next two are the province code, and the last four correspond to the rank of the fire (position according to year and province). Following, a detailed description of the form is presented:

General information of the fire

This sub-form contains information regarding the fire as a whole, including:

- Location data: Autonomous region, province, county, municipality, other small scale administrative divisions and UTM coordinates of the ignition point.
- Time data: fire detection time, terrestrial extinction service arrival time, airborne extinction service arrival time, helicopter extinction service arrival time, time until the fire is controlled, and fire suppression time.
- Detection: detection procedure and origin place.
- Ignition causes: differences between known and supposed cause and then into the most likely ignition source according to 40 categories of causes, which are also aggregated into six categories: natural (lightning), human (negligence, accident or arson), restarted fires and unknown or unidentified fires.
- Danger circumstances at fire start time: meteorological data, fuel model, danger rating index.
- Fire suppression methods: firefighting personal and equipment used for fire extinction.
- Fire suppression techniques.

- Losses: number harm and deceased persons, affected forest area (differentiating between with or without tree species), affected non-forest area, qualitative evaluation of environmental losses and infrastructures.
- Impact on Natural Protected Areas: area's ID and affected Surface.

Forest specific information

This sub-form provides detailed information, collect for each affected municipality and property for each single fire event in the General Information sub-form:

- Location data: municipality, forest legal condition and forest ID.
- Tree-forest affected area: affected tree species, silvicultural status, average tree area, affected area and affected canopy cover.
- Shrubland-forest affected area.
- Grassland affected area.
- Factors to calculate losses in timber products and repopulation. Includes the affected timber volumes, prices of standing timber before and after the fire and the price for each burnt mature tree species affected.
- Factors for the calculation of losses such as cork, resins, fruits, mushrooms, firewood, grazing and hunting.
- Assessment of income losses and extinction expenses.

3.1.1. Human-caused fire ignition: dependent variable for wildfire modeling

The dependent variable –high/low wildfire occurrence– was built from the Spanish EGIF (General Statistics of Wildfires) database from 1988 to 2007. The spatial distribution of fire occurrence (308,893 fires in the period from 1988 to 2007) was developed through a combination of the 10x10 km grid, a digital map of Spanish municipalities and the boundaries of the forest area. More specifically the ignition location procedure is based in the method developed by de la Riva *et al*. (2004). This method is widely recognized and has been used in many wildfire assessment research works in the Spanish territory such as Amatulli *et al*. (2007), Chuvieco *et al*. (2012; 2010). The method proposes a multi-step procedure which successively refines and decreases the potential location area of the ignition points by ruling out areas where the fire could not have occurred. Firstly it starts in the 10x10 grid with a potential location area of 100 km2. Then this area is decreased by intersecting with the boundaries of the municipality origin of the fire. Finally, the location area is restricted to the forest perimeter –since the ignition location of every wildfire is expected to be in the forest area– to determine the final potential location area. This process leads to a significantly smaller area where the ignition points are then randomly distributed. This allowed us to calculate fire density maps with a spatial resolution of 1x1 km by overlapping the final ignition points cloud and a 1x1km UTM grid (which perfectly fits the 10x10 -grid). Figure 2 illustrates this procedure. Recent studies have commented that predictions from fire simulations based on random ignitions may produce unrealistic results because the spatial distribution of ignition locations, whether human-caused or natural, is non-random (Bar Massada *et al*., 2011). However, the lack of explicit location data for wildfire events, especially in the first years of the EGIF dataset, made it impossible to generate a realistic set of locations. On the other hand, in many cases where coordinates have been assigned, the final location seems to be unreliable because it corresponds with unexpected sites such as the corner of the UTM grid or outside the forest area, which are more likely to be false.

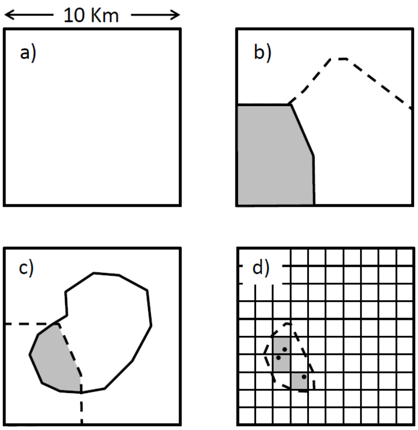

Figure 2. Procedure for ignition points location. Potential location area is grey-colored. a) 10x10 km ICONA grid; b) municipality intersection; c) forest area intersection; d) random point location and intersection with 1x1 km grid

The final dependent variable was created on a conceptual framework which assumed that there were no true cases of fire absence. In ignition data, most or all of the fire occurrences are accounted for, which may make it seem as if all other locations in the landscape have no fires. In this context, most previous attempts at fire occurrence modeling had used background subsets of “no occurrence” during the analyzed time span, considering them to be true cases of fire absence (e.g., Chuvieco *et al*., 2010; Padilla *et al*., 2011). However, the fact that these areas did not experience an ignition event during the temporal span of the data set does not mean that they could not feasibly support an ignition event in the future, or that they never ignited in the past (Bar Massada *et al*., 2012). In line with this reasoning, the dependent variable was developed by classifying the occurrence values into two categories: high occurrence (presence; 27956 points) in locations with two or more fires, and low occurrence (pseudo-absence or background; 28188 points) in locations with only one fire. The authors thought that the consideration of low-occurrence locations as pseudo-absences was more realistic than the creation of random background subsets. The fact that these areas have experienced only experienced one fire event in a long time span (20 years), means that their characteristics are strongly related with low fire frequencies.

It should be noted that the dependent variable used to calibrate the GWR models (see Section 4.2) was constructed using human-caused fires over 5 ha in size were selected (8727 fires). This is mainly due to the high computation power demanded by current GWR software and statistical packages.

3.1.2. Anthropogenic factors in fire ignition: explanatory variables for wildfire modeling

It is common, both in literature on this topic and fire history statistics, to deal with the classification of anthropogenic fire ignition factors by grouping them in two groups, depending on the existence of intentionality. The first would include all those factors directly or indirectly related to fire start in which no intentionality is found but rather ignition is associated to negligence. These fires are usually linked to traditional activities in rural areas as well as to socio-economic transformations in the last decades. The second group is directly related to factors that generate certain sort of conflict which, in turn, can lead to the intended start of a fire (Leone *et al*., 2003; Martínez *et al*., 2004).

The explanatory variables for wildfire modeling were selected on the basis of experience in models at regional and national scale (Chuvieco *et al*., 2010; Martínez *et al*., 2009; Vilar del Hoyo *et al*., 2008) and classified according to this typology of the affecting factor, as follows:

1. Factors related to socioeconomic transformation.
   1.1. Abandonment of traditional activities in wildland/rural areas. Accumulation of forest fuel.
      1.1.1. ***People employed in the primary sector***. Obtained at the municipal level from the Agricultural Census 1999 of the Spanish Statistics Institute (INE).
   1.2. Abandonment of traditional activities in wildland/rural areas especially in privately owned forests with no prospect of economic profit. Little or no interest in forest conservation.

1.2.1. ***Forestry area in public utility***. Delimitation of the area occupied by forestry areas included in the public utility catalog.

1.3. Increasing use of forest as a recreational resource. More frequent visits to forests.

1.3.1. ***Tracks***. Area occupied by the buffer 200 meters either side of the forestry track network. Obtained from BCN200.

1.4. Human presence, population increase and urban growth. Increased pressure on wildlands

1.4.1. ***Wildland-Urban Interface (WUI)***. Area occupied by the buffer 200 meters from the line of contact to the forest area. Constructed from the Spanish Forestry Map 1:200000 (MFE200).

1.4.2. ***Changes in demographic*** *potential, 1991-2006* (Calvo and Pueyo, 2008). Variation rate between the demographic potential in 1991 and 2006.

2. Factors related to traditional economic activities in rural areas.

2.1. Aged rural population. Traditional management methods.

2.1.1. ***Percentage of owners of holdings aged over 55 years.*** Obtained at the municipal level from the Agricultural Census 1999 of the Spanish Statistics Institute (INE).

2.2. Agriculture. Use of fire to clear harvesting waste, cleaning along borders of cropland.

2.2.1. ***Wildland-agricultural interface (WAI)***. Area occupied by the buffer 200 meters from the line of contact to the forest area. Constructed from the Spanish Forestry Map 1:200000 (MFE200).

2.3. Cattle grazing. Possible fire to maintain herbaceous vegetation.

2.3.1. ***Extensive livestock***. Obtained at municipal level from the Agricultural Census 1999 of the Spanish Statistics Institute (INE).

2.3.2. ***Wildland-grassland interface (WGI)***. Area occupied by the buffer 200 meters from the line of contact to the forest area. Constructed from the Spanish Forestry Map 1:200000 (MFE200).

3. Factors that could cause fire mainly by accident or negligence.

3.1. Electric lines. Possible cause of ignition by accident.

3.1.1. ***Power lines***. Area occupied by the buffer 50 meters either side of the high, medium, and low voltage power network. Obtained from BCN200.

3.2. Engines and machines working in or close to forested areas Possible cause of ignition by accident or negligence.

3.2.1. ***Density of agricultural machinery (DAM).*** Obtained at municipal level from the Agricultural Census 1999 of the Spanish Statistics Institute (INE).

3.3. Existence of roads, railroads, tracks, and accessibility. Greater human pressure on wildland.

3.3.1. ***Railroads***. Area occupied by the buffer 200 meters either side of the railroad network (excluding the high-speed network). Obtained from a digital cartographic database (BCN200).

3.3.2. ***Tracks***.

3.3.3. ***Changes in demographic potential 1991-2006***

4. Factors that could help prevent fires.

4.1. Protected area. Increasing concern about forest protection.

4.1.1. ***Protected areas***. Delimitation of the area occupied by protected natural areas and the *Natura 2000* network.

5. Factors that generate conflicts, and which could lead to intentional starting of fire and/or facilitating its spread.

5.1. Changes from forest use. Possible cause of arson.

5.1.1. ***Changes in land cover***. Loss or increase of area covered by forest or semi-natural regions. Obtained from the Corine Land Cover 1990 and 2006 maps.

5.2. Fire industry. Fire started to gain income, work, payment or subsidies from fire prevention or fighting and in restoration of land affected by fire.

5.2.1. ***Unemployment rate***. Obtained for municipal level in 2007 from the population and housing census 2001 (updated to 2007) of the Spanish Statistics Institute (INE).

3.3. Ecological vulnerability

3.1.3. Characterization of fire-affected plant communities

Some plant species are better adapted to fire than others and either better resist the impacts of fire or recuperate more quickly, depending on the regeneration strategies and horizontal and vertical continuity (Baeza and Roy, 2008). Plant characterization is made in terms of pre-fire structure of the dominant plant community (grassland, shrubland, or trees), and post-fire regeneration strategy of the dominant plant community (obligate resprouter or seeder). Initially, the assessment affected plant communities is made from lists of dominant plant species in the Forest Map of Spain (obtained from the

Biodiversity Data Bank of the Spanish Ministry of Agriculture, Food and Environment), giving an individual characterization, in terms of their structure and regeneration strategy, of more than 500 species. Plant characterization is based on the experience of the authors (de la Riva *et al*., 2008; Duguy *et al*., 2012) and several studies of post-fire vegetation and response (e.g. Baeza and Roy, 2008; Barbéro *et al*., 1998; Buhk *et al*., 2007; Martinez, 2005; Pausas *et al*., 2004; Tárrega and Luis-Calabuig, 1989; Trabaud, 1990, 1998, 2002; Vera de la Fuente, 1994). It should be noted that we did not find all the information required for the characterization of all species in Spain; as a result, several species are classified according to the authors' criteria alone.

3.1.4. Factors influencing vegetation's post-fire dynamics

The main trends of degradation induced by fire may include permanent changes in the floristic composition of the plant community, reduction of vegetation cover, biomass loss, and alteration of landscape patterns. Forest fires can also produce changes in floristic and physiognomic parameters of vegetation through their impact on the physical and chemical properties and nutrient availability of soil (Vallejo *et al*., 2009). After the burning of vegetation, the contribution of ash to the soil temporarily increases the availability of some nutrients (P, Mg, K, Ca, Na). This initial fertilization depends on the severity of the fire and the amount of biomass (fuel) prior to the fire. However, other nutrients such as nitrogen may volatilize or be washed away as a result of wind or water erosion post-fire (Neary *et al*., 2009; Shakesby and Doerr, 2006). In addition, the loss of vegetation cover after fire increases surface erosion because the bare soil is exposed to raindrop impact and surface runoff, especially in the first months after burning (Giovannini *et al*., 2001; Inbar *et al*., 1998). However, the post-fire dynamic of plant communities is conditioned by the environmental conditions such as the amount of water available for plant development, the rainfall regime, the site-specific conditions (slope, aspect…) among others.

The influence of the environmental conditions on the ability to recover from fire that plant communities have is addressed here by taking into account the amount of water after the fire, also considering soil conditions. Water availability for vegetation development (from rainfall), and soil loss as a consequence of loss of canopy cover are parameters that mainly depend on the characteristics and temporal evolution of the climatic conditions (Certini, 2005), influencing plants by modifying the amount of available nutrients and water or soil chemical composition (Shakesby and Doerr, 2006). Therefore, climatic conditions and soil loss are considered key parameters when modeling relationships between wildfire and vegetation (Daly *et al*., 2000; Lenihan *et al*., 2008).

We derived water availability from the precipitation data reported in the Vegetation Series map of Spain (Rivas Martínez, 1987). This map was initially developed to delineate areas of recognized vegetation units (also referred to as “series”) to determine the great diversity of forest ecosystems in Spain. However, each of the different series was also assigned a typical rainfall category (arid, semiarid, dry sub-humid, humid, and hyper-humid) based on annual local precipitation, which enables the assessment of water availability on that basis.

Soil erosion is another major negative outcome of forest fires, particularly in the Mediterranean region (San-Miguel-Ayanz *et al*., 2012b). Within Europe, the risk of water-driven soil erosion is particularly high in the Mediterranean region where autumn rain storms often follow summer wild fires (Pausas and Vallejo, 1999). The susceptibility of a burnt area to soil erosion depends on the intensity of the fire and the degree to which the vegetation cover is removed (San-Miguel-Ayanz *et al*., 2012b). The Pan-European Soil Erosion Risk Assessment model (PESERA, Kirkby *et al*., 2004) was used in order to include the influence of soil erosion. PESERA is a spatially distributed model at 1x1 km resolution for quantification of water soil erosion.

However, data from PESERA models only accounts for pre-fire erosion rates, which means that it has to be adapted to proper reflect post-fire erosion losses. To this end we selected the ERMiT model (Robichaud, 2006). The ERMiT (http://forest.moscowfsl.wsu.edu/cgi-bin/fswepp/ermit/ermit.pl) model integrates information on climate indicators, soil (texture), topography (slope and slope length), plus the type of vegetation affected and the severity level of the fire, thus allowing simulations to assess fire-caused increases in erosion rates. The model uses a probabilistic approach that incorporates temporal and spatial variability in weather, soil properties, and burn severity for forests, rangeland, and chaparral hill slopes. ERMiT allows calculation of the percentage increase in the pre-fire erosion rate (PESERA) in several vegetation communities, which are characterized in terms of climate, soil, and topography indicators, given a specific fire severity (high severity in our case).

On the other hand, climate trends are a key factor in vulnerability assessment (González *et al*., 2010). Most climate change predictions imply increased air temperatures and less summer rainfall for the Mediterranean basin (Hertig, 2008; Schröter *et al*., 2005). Adverse climatic conditions (i.e., dryer conditions) in many of the areas affected by fires may have caused lower rates of post-fire vegetation recovery (San-Miguel-Ayanz *et al*., 2012a). Hence, the observed changes in temperature and precipitation provide indicators of the potential change of the biome of an ecosystem (González *et* *al*., 2010). Data about rainfall trends is obtained from de Luis *et al*. (2010). In that study, the spatial variability of seasonal precipitation regimes in the Iberian Peninsula were calculated for a temporal period of observations of 50 years from 1946 to 2005, using the Mann–Kendall test. The spatial variability of the seasonal trends is characterized according to the sign and significance level of the observed trends. As the rainfall trends were calculated only at seasonal level, we used winter trends to weight water availability, considering this to be the most effective season for plants to capture water, due to low potential evapotranspiration. We used autumn trends for soil erosion weighting, as this is the most critical season due to the dryness of the soil following summer (Pausas and Vallejo, 1999), the decreased vegetation cover from the loss of leaves in deciduous communities, and torrential rains (de Luis *et al*., 2010).

CHAPTER 4. METHODS

This chapter presents and describes in depth the methods applied to develop this PhD research work. Firstly, the trend detection procedures used in the European scale trend analysis are introduced (section 4.1). Then, the regression methods are presented, starting with classical regression techniques for probabilistic wildfire modeling, followed by a local regression approach, later introducing the machine learning algorithms (sections 4.2, 4.3 and 4.4). After that, cluster and outlier techniques are explained (section 4.5). Finally, the method for quantitative assessment of ecological vulnerability is described (section 4.6).

4.1. Trend detection tests

4.4.1. Mann-Kendall test

Temporal trends were analyzed for the study period 1985-2009. The observed trends were assessed with the Mann-Kendall test, which is a non-parametric statistical test appropriate to identify trends in time series data (Kendall, 1975; Mann, 1945) and commonly used in environmental research (e.g. Río *et al.*, 2011 or Todeschini 2012). Mann-Kendall is a rank non-parametric test that was developed by Mann (1945) and Kendall (1975), and it is suited for detecting linear or non-linear trends (Hisdal *et al.*, 2001; Wu *et al.*, 2008). In this test, the null (H_0) and alternative hypotheses (H_1) are equal to the nonexistence and existence of a trend in the time series of the observational data, respectively. The magnitude of the change was subsequently assessed by means of the Sen's slope (Sen, 1968), a nonparametric alternative for estimating the median slope joining all possible pairs of observations, which allows the comparison of the magnitude of the detected trends.

The computational procedure for the Mann Kendall test considers the time series of n data points and T_i and T_j as two subsets of data where i = 1,2,3,…, n-1 and j = i+1, i+2, i+3, …, n. The data values are evaluated as a sorted time series. Each data value is compared with all subsequent data values. If a data value from a later time period is higher than a data value from an earlier time period, the statistic S is incremented by 1. On the other hand, if the data value from a later time period is lower than a data value sampled earlier, S is decremented by 1. The net result of all such increments and decrements yields the final value of S (Drapela and Drapelova, 2011).

The Mann-Kendall S Statistic is computed as follows:

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} sign\ (T_j - T_i)$$

$$sign\left(T_j - T_i\right) = \begin{cases} 1\ if\ T_j - T_1 > 0 \\ 0\ if\ T_j - T_i = 0 \\ -1\ if\ T_j - T_1 < 0 \end{cases}$$

where T_j and T_i are the annual values in years j and i, $j > i$, respectively (Motiee and McBean, 2009).

4.4.2. Alternative trend detection procedures

Temporal trends were also assessed using alternative tests for trend detection to determine the variability in the results depending on the trend detection procedure and the robustness of the results obtained with the proposed Mann-Kendall test. As alternative procedures we used two nonparametric tests –Spearman's Rho and Cox-Stuart test– and one parametric test –t-test–. The comparison between the results obtained with the Mann-Kendall test and the alternative procedures was carried out by comparing the resulting positive, negative and non-significant trends through the Cohen's Kappa agreement values.

Spearman's Rho

The Spearman's Rho (SR) test is a simple method, similar to the Mann-Kendall method, with uniform power for linear and non-linear trends. The SR is commonly used to verify the absence of trends (Dahmen and Hall, 1990; Tonkaz *et al*., 2007). In this test, the null hypothesis (H_0) is that all the data in the time series are independent and identically distributed, while the alternative hypothesis (H_1) is that increasing or decreasing trends exist (Cox and Stuart, 1955; Yue *et al*., 2002).

Cox-Stuart test

Cox-Stuart test (CS, Cox and Stuart, 1955) is a sign test based on specific paired comparisons. The CS test is useful for detecting positively or negatively sloping gradual trends in a sequence of independent measurements on a single random variable. The null hypothesis is that no trend exists. If the null hypothesis is accepted, the result indicates that the measurements within the ordered sequence are identically distributed (McCuen, 2003).

T-test

The t-test for trend detection is a parametric method based in the comparison of the means for two different samples (periods) through an ANOVA procedure. The magnitude of change is measured by the difference in sample means between the two periods. Parametric tests assume that the random variable is normally distributed and homogeneous variance. The t-test for trend detection is based on linear regression, and therefore checks only for a linear trend.

4.2. Binary logit regression

Binary logit Regression (LR) models are statistical models which provide insights into the relationship between a qualitative dichotomous dependent variable, and one or more independent explanatory variables, whether qualitative or quantitative. More specifically LR allows computing the probability that each individual belongs to one of the groups that defines the dependent variable. Thus, LR are either explicative and predictive models as they enable both the calculation of the relationship between the dependent and explanatory variables as well as calculate the probability of having a particular value of the dependent variable given a set of explanatory factors. The LR model has a number of assumptions, such as assuming no linear relationship between the dependent and independent variables. Moreover, the dependent variable need not follow a normal distribution and be homoscedastic (homogeneity of variance). This technique also assumes that the error terms are independent and does not take into account the effects of interaction between the variables; given no collinearity among the explanatory variables. When the independent variables have a great the LR model is not able to distinguish which part of the dependent variable is explained by either variable. For increasing the correlation between the variables, the standard error of coefficients increases. Multicollinearity does not change the estimated coefficients, but their safety.

LR is a commonly used technique for probabilistic explanation of human-caused occurrences (Chuvieco *et al*., 2010; Martínez, 2004; Martínez *et al*., 2009; Vasconcelos *et al*., 2001; Vega-Garcia, 1996).

The mathematical expression of LR models is:

$$y_i = \frac{e^{(\beta_0+\beta_1 x_{1i}+\ldots+\beta_k x_{ki})}}{1+e^{(\beta_0+\beta_1 x_{1i}+\ldots+\beta_k x_{ki})}}$$

In this PhD thesis, the LR model was developed using a *forward stepwise* procedure in which the explanatory variables were introduced into the model one by one according to the resulting improvement in the model, as measured by the Akaike Information Criterion (AIC).

4.3. Geographically weighted regression

GWR is a statistical technique for exploratory spatial data analysis developed within the framework of Local Spatial Models or Statistics. Local models could be inferred as the spatial disaggregation of global statistics whose main characteristic is the fact of being calibrated from a set of spatially limited samples and hence yielding local regression parameters estimates (Fotheringham *et al*., 2002). Therefore, GWR techniques extend the traditional use of global regression models, allowing calculation of local regression parameters. From a mathematical standpoint a conventional GWR is described by the following equation:

$$y_i = \sum_k \beta_k \,(u_i, v_i)\; x_{k.i} + \varepsilon_i$$

where y_i , $x_{k,i}$ and ε_i are, respectively, dependent variable, kth independent variable, and the Gaussian error at location i; (u_i,v_i) is the x-y coordinate of the ith location; and coefficients $\beta\,(u_i,v_i)$ are varying conditionals on the location.

Such modelling is likely to attain higher performance than traditional regression models, and reading the coefficients can lead to a new interpretation of the phenomena under study. However, GWR models are not just a simple local regression model like i.e. moving window regressions. In a moving window example, a region is described around a regression point and all the data points within this region (neighborhood) or window are then used to calibrate a model. This process is repeated over all the regression points obtaining as result a set of local regression statistics. However, in this example each point within the neighborhood is equally considered for regression purposes, no matter its distance to the target regression point. GWR overcomes this limitation by applying a distance weight pattern; hence, data points closer to the regression point are weighted more heavily in the local regression than data points farther away are (Figure 3).

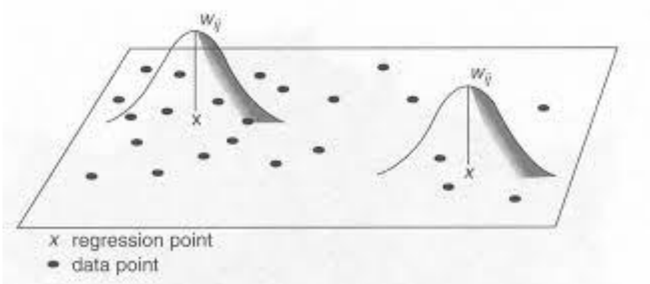

Figure 3. GWR distance weight pattern (Fotheringam *et al*., 2002).

Determining the size of the neighborhood region (bandwidth calibration) is a crucial step since regression output will vary significantly according to this parameter's value. In this regard, two different approaches for bandwidth calibration are available in any GWR model: (i) fixed kernel, which specifies a distance threshold equally for each regression point; and (ii) adaptive kernel, which specifies the number of neighbor (data points) to be considered for each regression points. In the first case, number of neighbors will probably vary from one regression point to another according to the spatial point pattern. In the case of adaptive kernel it is just the opposite, changing the distance threshold to fit the number of data points. In general lines, fixed kernels should is appropriate in a scenario where the point cloud is regularly distributed over the space and adaptive approach in the case of spatially clustered patterns. Finally, the optimum distance bandwidth value or the optimum number of neighbors could be determined in two ways: by minimizing the square of the residuals (Cross-Validation, Cleveland, 1979) or by minimizing the Akaike Information Criterion (AIC, adapted for GWR by Hurvich *et al*. 1998).

On the other hand, it should be noted that basic GWR is based on a linear regression model. Accordingly it assumes a Gaussian distribution for the dependent variable. This implies that the dependent variable is symmetrical around some mean value and it admits values anywhere in the interval (-∞,∞). However, there are situations where these properties are not good models of reality. This issue was firstly addressed in the early 1970s by *Generalised Linear Models* (GLM, McCullagh, 1992; Nelder and Wedderburn, 1972). GLM extend the basic regression model allowing other probability distributions for the dependent variable (i.e. logit or Poisson distributions) and consequently different properties. GLM have been also incorporated to GWR to extend its functionality, leading to GWGLM like Geographically Weighted Logistic Regression (GWLR) and Geographically Weighted Poisson Regression (GWPR) approaches.

The methodology for modeling human causality in forest fires is based on GWLR techniques. Logistic regression has been traditionally used to model presence/absence phenomena as is the case of wildfire occurrence. Accordingly, it is appropriate to explore its GWR variety. Like global logistic regression models (GLR), GWLR are statistical models that provide insights into the relationship between a qualitative dependent variable, dichotomous in our case, and one or more independent explanatory variables, whether qualitative or quantitative. Therefore, its development requires on the one hand a binary dependent variable, in this case the high/low occurrence of fires, and secondly a set of predictor variables. Taking as a starting point the typical equation of the logistic regression:

$$y_i = \frac{e^{(\beta_0+\beta_1 x_{1i}+...+\beta_k x_{ki})}}{1+e^{(\beta_0+\beta_1 x_{1i}+...+\beta_k x_{ki})}}$$

The mathematical expression of its geographically weighted version is reconstructed as follows:

$$y_{(u_i,v_i)} = \frac{e^{(\beta_0(u_i,v_i)+\beta_1(u_i,v_i)x_{1i}+...+\beta_k(u_{ki},v_{ki})x_{ki})}}{1+e^{(\beta_0(u_i,v_i)+\beta_1(u_i,v_i)x_{1i}+...+\beta_k(u_{ki},v_{ki})x_{ki})}}$$

where (u_i, v_i) are the location coordinates in space of point i.

As in the case of basic GWR, the use of GWLR models allows obtaining regression coefficients whose values vary spatially, thus obtaining a different set of regression coefficients for each location in the study area. In addition to the regression coefficients, the GWLR model calculates several useful statistical parameters to analyze each of the explanatory variables, such as the value of the Student t test (used to determine the level of significance) and the local R^2 value (i.e., the R^2 value of the resulting model at the point where the value is referenced and its neighbors), among others. However, GWLR does not allow estimation of regression coefficients in locations where there is no observation. In order to overcome this limitation and apply the model to the entire area of study, the regression coefficients are interpolated using the Local Polynomial Interpolation method in ArcGIS 10.1 (1st order polynomial and exponential kernel function), thus preserving the original values of locations with observations and hence the internal consistency of the model.

4.4. Machine learning algorithms

Machine learning (ML) models have shown their predictive accuracy in data mining and other fields. Prior studies have also proposed ML algorithms to model the spatial distribution of wildfire occurrence or ignition (Regression Trees, Artificial Neural Networks and Random Forest. However, these methods have not been widely used to model human-caused wildfire occurrence at a regional scale or for large occurrence datasets; this is therefore the main goal of this work. This topic will be addressed in greater depth by exploring other stochastic (tree-based) and deterministic ML algorithms and their application to the Spanish territory. Specifically, the performance of Random Forest (RF), Boosted Regression Trees (BRT), and Support Vector Machines (SVM) has been explored, and their outcomes have been compared with those from binary logistic regression (LR).

4.4.1. Random Forest

The Random Forest (RF) is an ensemble classifier using decision trees as base classifier. The main drawback of traditional tree-based algorithms (such as Regression Trees) is that models are that this approach is not entirely robust because each division can involve a set of variables with similar discriminatory power. Therefore, small changes in the data can generate very different models. To avoid such problems, researchers have recently shown interest in ensemble learning methods. These methods generate many classifiers (trees) and enable grouping of the results in a final classification. Two examples of well-known ensemble methods are bagging and boosting (Breiman, 1996; Hastie, 2009; Hernández, 2004; Sierra, 2006). Bagging is a technique designed to create training data sets resampled randomly with replacement of original data, i.e., without removing the selected data set before selecting the next subset. Thus, data may be used more than once to train individual classifiers. This property makes bagging methods less sensitive to slight variations in the input data (training changes, outliers, noise ...) and at the same time increases the accuracy of classifications (Breiman, 2001).

The RF algorithm consists of a collection of simple tree predictors, each capable of producing a response when presented with a set of predictor values. For classification problems, this response takes the form of a class membership, which associates, or classifies, a set of independent predictor values with one of the categories present in the dependent variable. Alternatively, for regression problems, the tree response is an estimate of the dependent variable given the predictors. The RF algorithm was proposed by Breiman (2001) and adds an element of randomness to bagging, increasing the diversity of decision trees by growing them from different subsets.

Besides generating each decision tree using a subset of different training elements in each iteration, RF changes the way that the decision tree is generate. In the creation of a decision tree in the CART algorithm, each node is split using the best threshold for all predictors, while in RF, the nodes are divided using the best variables from a random sample. This modification, although somewhat counterintuitive, has proven to be a strategy that gives very good results compared to other classifiers with completely different approaches or to other tree-based algorithms (Liaw and Wiener, 2002). For the final classification of each element, each generated random tree provides a simple vote, and the algorithm assigns the response that received the most votes (Liaw and Wiener, 2002).

From an operational point of view RF can be parameterized (R package *randomForest*) according to the number of trees averaged in the ensemble forest (*ntrees*), the number of predictor variables randomly selected at each iteration (*mtry*), and the minimum number of observations at end nodes (*nodesize*), which can decrease the length of nodes in tree branches and simplify trees. The random forests algorithm (for both classification and regression) works as follows (Liaw and Wiener, 2002):

1. Draw *ntree* bootstrap samples from the original data.
2. For each of the bootstrap samples, grow an unpruned classification or regression tree, with the following modification: at each node, rather than choosing the best split among all predictors, randomly sample *mtry* of the predictors and choose the best split from among those variables (Bagging can be thought of as the special case of random forests obtained when *mtry* = p, the number of predictors).
3. Predict new data by aggregating the predictions of the *ntree* trees (i.e., majority votes for classification, average for regression).

An estimate of the error rate can be obtained, based on the training data, by the following:

1. At each bootstrap iteration, predict the data not in the bootstrap sample (what Breiman calls "out-of-bag", or OOB, data) using the tree grown with the bootstrap sample.
2. Aggregate the OOB predictions. (On the average, each data point would be out-of-bag around 36% of the times, to aggregate these predictions). Calculate the error rate, and call it the OOB estimate of error rate.

4.4.2. Boosted Regression Trees

Boosted Regression Trees (BRT) is a technique, which draws on insights and techniques from both statistical and ML traditions. The BRT approach differs fundamentally from traditional regression methods that produce a single best model. Instead, BRT uses boosting to combine large numbers of relatively simple tree models to optimize predictive performance (Elith, 2008; Leathwick, 2006; Leathwick *et al.*, 2008). The boosting approach used in BRT places its origins within ML (Schapire, 2003), but subsequent developments in the statistical community have reinterpreted it as an advanced form of regression (Friedman *et al.*, 2000).

BRT uses two algorithms: regression trees for classification and regression (same as RF), and boosting for combining a collection of models (Elith, 2008). The main difference between BRT and RF is found in the way they ensemble the regression trees to produce the final model. While RF is based on bagging methods, BRT uses the boosting approach.

Boosting is a method for improving model accuracy, based on the idea that it is easier to find and average many rough rules of thumb, than to find a single, highly accurate prediction rule (Schapire, 2003). Related techniques – including bagging, stacking and model averaging – also build, then merge results from multiple models, but boosting is unique because it is sequential: it is a forward, stagewise procedure. In boosting, models (e.g. decision trees) are fitted iteratively to the training data, using appropriate methods gradually to increase emphasis on observations modelled poorly by the existing collection of trees. Boosting algorithms vary in how they quantify lack of fit and select settings for the next iteration.

The original boosting algorithms such as *AdaBoost* (Freund and Schapire, 1996) were developed for two-class classification problems. They apply weights to the observations, emphasizing poorly modelled ones, so the ML literature tends to discuss boosting in terms of changing weights.

Here, though, we focus on regression and the intuition is different. For regression problems, boosting is a form of 'functional gradient descent'. Consider a loss function – in this case, a measure (such as deviance) that represents the loss in predictive performance due to a suboptimal model. Boosting is a numerical optimization technique for minimizing the loss function by adding, at each step, a new tree that best reduces (steps down the gradient of) the loss function. For BRT, the first regression tree is the one that, for the selected tree size, maximally reduces the loss function. For each following step, the focus is on the residuals: on variation in the response that is not so far explained by the model. For example, at the second step, a tree is fitted to the residuals of the first tree, and that second tree could contain quite different variables and split points compared with the first. The model is then updated to contain two trees (two terms), and the residuals from this two-term model are calculated, and so on. The process is stagewise (not stepwise), meaning that existing trees are left unchanged as the model is enlarged. Only the fitted value for each observation is re-estimated at each step to reflect the contribution of the newly added tree. The final BRT model is a linear combination of many trees that can be thought of as a regression model where each term is a tree (Elith, 2008).

The calibration of a BRT model can be tuned using several parameters (R package *dismo*) such as the number of nodes in a tree (*tree complexity*), the contribution to the model of each tree (*learning rate*), the proportion of data to be selected at each step (*bag fraction*), and the average number of trees in the ensemble forest (*ntrees*). According to Elith *et al*. (2008) a decreasing (slowing) learning rate increases the value of *ntrees* required, and in general, a smaller value of learning rate (and a larger value of *ntrees*) is preferable, conditional on the number of observations and the time available for computation.

4.4.3. Support Vector Machines

Support Vector Machines (SVM) is a supervised learning model with associated learning algorithms that analyze data and recognize patterns, used for classification and regression analysis. SVM are a very specific class of algorithms, characterized by usage of kernels, absence of local minima, sparseness of the solution and capacity control obtained by acting on the margin, or on number of support vectors. The SVM algorithm is based on making highly reliable predictions, even at the risk of making some mistakes. To this end, SVM tries to find the optimal hyperplane of separation between the classes, i.e. the plane in which the separability between classes is a maximum (see Figure 4). The examples located on this hyperplane are called support vectors. These examples are the most difficult to classify since they have lower separability. In the simplest case, two classes in a two-dimensional space in which the data are linearly separable, the optimal hyperplane would be defined by a straight line. For a more detailed description of SVM operation, see (Vapnik, 1995, 1998).

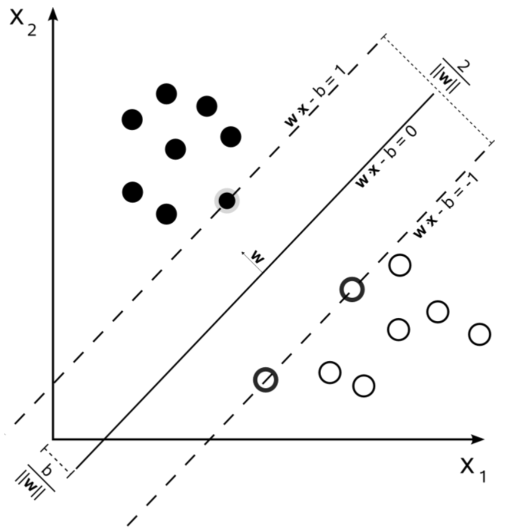

Figure 4. SVM example (source: http://en.wikipedia.org/).

A SVM model requires a large number of parameters (R package *kernlab*) to be optimized: kernel functions (linear, polynomial, sigma, or radial basis), cost, the gamma of the kernel function (except the linear kernel), the bias of the kernel function (applicable only to the polynomial sigmoid kernel), and finally the polynomial degree (applicable only to the polynomial kernel). For this reason, the optimization of an SVM model is more complicated than optimization of RF or BRT.

4.5. Spatial cluster and outlier analysis

Indicators of spatial association are statistics that evaluate the existence of clusters in the spatial arrangement of a given variable. Cluster and Outlier Analysis, and more specifically the Anselin's Local Moran's (Anselin, 1995) is a spatial association technique which also enables identifying and allocating Hot Spot areas as well as characterizes its typology of cluster.

In the analysis of spatial association, it has long been recognized that the assumption of stationarity or structural stability over space may be highly unrealistic, especially when a large number of spatial observations are used. Spatial structural instability or spatial drift has been incorporated in a number of modeling approaches. Upon this general idea, local indicators of spatial association allow for the decomposition of global indicators, such as Moran's I, into the contribution of each individual observation. From an operational standpoint, the Anselin's Local Moran`s identifies clusters of features with values similar in magnitude given a set of weighted features. The index also identifies spatial outliers, calculating a Local Moran's I value, a Z score, a p-value, and a code representing the cluster type for each feature. The Local I Moran's is calculated as follows:

$$I_i = \frac{x_i - \bar{X}}{S_i^2} \sum_{j=1\ j\neq 1}^{n} w_{i,j}(x_i - \bar{X})$$

where x_i is an attribute of the feature, $\bar{X}$ is the mean of the corresponding attribute, $w_{i,j}$ is the spatial weight between feature *i* and *j*, and:

$$S_i^2 = \frac{\sum_{j=1\ j\neq 1}^{n} w_{i,j}(x_i - \bar{X})^2}{n-1} - \bar{X}^2$$

with *n* equating to the total number of features.

4.6. Quantitative assessment of ecological vulnerability

The methodology for estimating the post-fire vegetation recovery time (RT) is based on calculating the regeneration time of plant communities. The method is based on a map algebra procedure which allows overlying information relating the different parameters that control the process on a spatial basis. Specifically, the proposed method is an inductive model, based on the necessity of an easy-to-use approach which allows informing forest management authorities.

To do this, an initial RT (recovery time under optimum conditions, RTOC, see Section 3.1.3) is assigned according to the dominant plant communities' structure (grassland, shrubland, or trees) and regeneration strategy (resprouter or seeder). The increase in time is then calculated by introducing the influence of plant species growth constraints (PSGC, see Section 3.1.4): water availability from annual rainfall, soil erosion due to loss of protective vegetation cover, and seasonal rainfall trends, which influence both water availability and soil loss mainly after the fire. The influence of water availability and soil erosion is introduced as a weight factor of RTOC. In turn, seasonal rainfall trends, specifically winter and summer trends, are introduced by weighting water availability and soil loss. RTOC is assigned based on experts' criteria supported by a literature review (detailed later), in a scenario of optimal conditions for vegetation development. This means that we consider that the recovery process takes place with no constraining factors for vegetation development, such as water and/or nutrient availability, chemical alteration of the soil, or fire recurrence.

To apply the map algebra approach, the variables of the model were recoded into RT increase ratios and later transformed into a raster grid. The RT was calculated as the sum of RTOC and the time increase from the PSGC:

$$RT = RTOC + T_{Fw}T_w + T_{Fe}T_a$$

where T_{Fw} is the time increase from water availability, T_w is the winter rainfall trend weight, T_{Fe} the time increase from soil loss, and T_a is the autumn rainfall trend weight.

Once again, it should be emphasized that this RT is not a categorical value, rather an indication of the period needed to return to pre-fire conditions, since the main objective of this work is to develop a methodological framework to assess recovery time.

CHAPTER 5. TEMPORAL EVOLUTION OF NUMBER OF FIRES AND BURNT AREA

This chapter presents the results, discussion and main conclusions obtained from the temporal analysis of wildfires in the EUMed region. Several trend detection procedures have been applied to fire count and burnt area data in order to determine the temporal evolution of wildfires and, therefore, provide information about wildfires as a dynamic hazard.

An insight into spatial-temporal trends of fire ignitions and burned areas in the European Mediterranean countries

(Appendix D)

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Abstract

This paper presents an analysis of the fire trends in Southern European countries, where forest fires are a major hazard. Data on number of fires and burned area size from 1985 until 2009 were retrieved from the European Fire Database in the European Forest Fire Information System and used to study the temporal and spatial variability of fire occurrence at three different spatial scales: the whole European Mediterranean region, country level and province level (NUTS3). The temporal trends were assessed with the Mann-Kendall test and Sen's slope in the period 1985-2009. At regional (supranational) level, our results suggest a significant decreasing trend in the burned area for the whole study period. At country level, the trends vary by country, although there is a general increase in number of fires, mainly in Portugal, and a decrease in burned areas, as is the case of Spain. A similar behavior was found at NUTS3 level, with an increase of number of fires in the Spanish and Portuguese provinces and a generalized decrease of the burned area in most provinces of the region. These results provide an important insight into the spatial distribution and temporal evolution of fires, a crucial step to investigate the underlying causes and impacts of fire occurrence in this region.

Keywords: fire ignition; burned area; wildfire; trend test; Mann-Kendall.

1. Introduction

Fires are an integral component of ecosystem dynamics in European landscapes. However, uncontrolled fires cause large environmental and economic damages, especially in the Mediterranean region (San-Miguel-Ayanz *et al*., 2012). Particularly the area covered by Portugal, Spain, Italy, Greece and southern France is, by far, the most affected by wildfires.

According to European statistics (Schmuck *et al*., 2011), from 1980 until 2009 fires have burned an average of circa 480,000 hectares of land per year in this region alone, with an annual average of 50,000 occurrences. Recent changes in socio-economic models and climatic patterns have significantly affected the historical fire regime in Southern Europe (González *et al*., 2010) involving a potential damage far greater than that traditionally experienced (Pausas and Vallejo, 1999). In addition there appears to be increased chances of having an especially dramatic season, similar to those that several countries suffered in the last decade as a result of extreme heat waves (Spain 2000 and 2005; Portugal 2003 and 2005; Greece 2007). This increase in wildfire frequency, with its associated risks to the environment and society (Moreno *et al*., 2011), calls for a better understanding of the processes that control wildfire activity (Bar Massada *et al*., 2012). Similarly, the concern about wildfires is increasing worldwide due to its significant impacts on human life and property, ecosystems, and other valuable resources (Thompson *et al*., 2011).

Data on the number of fires and burned area in the European region has been collected since the 70's by each country, and compiled in the Fire Database of the European Forest Fire Information System (EFFIS). The EFFIS Fire Database (Camia *et al*., 2010) is a comprehensive system with data on fire events from over 25 countries in the European and Mediterranean regions. The analysis of the spatial and temporal trends of fires is crucial to understand the underlying causes of the fires and their environmental and socio-economic impacts, assuming a key role in fire prevention and management (Jesús San-Miguel-Ayanz *et al*., 2012). Moreover, a better knowledge on spatial patterns of fire occurrence and their relationships with its underlying causes becomes a necessity to make prevention efforts more efficient (Martínez *et al*., 2009). Thus, the purpose of this work is to analyze the spatial and temporal trends of fire frequency (number of fires) and burned area size, two essential components of the fire regimes. The temporal trends were assessed with the Mann-Kendall test and Sen's slope in the period 1985-2009 at three different spatial scales: regional, country level, and province level.

2. Materials and methods

The analysis was carried out at three different spatial scales: (i) at regional (supranational) level, considering the Euro-Mediterranean region as a whole, with the purpose of characterizing its fire regimes, known to be markedly different from the rest of Europe. The region under study, shortly referred to as EUMed in what follows, comprises Portugal, Spain, France, Italy and Greece; (ii) at country level, by analyzing the data of each country individually in order to assess differences between countries that may depend on national settings and policies; and (iii) at province level (NUTS3), to investigate the potential influence of local environmental and socio-economic conditions. Trends were analyzed using the R statistical software, an open-source statistical programming language developed as a large collaborative project by statisticians from different countries and disciplines (R Development Team Core, 2008). Data on number fire events and burned area were retrieved from the EFFIS Database.

2.1. An overview to the EFFIS Database

European countries have collected information on forest fires since 1970s. However, the lack of harmonized information at the European level has prevented a holistic approach for forest fire prevention in the Region. The European Forest Fire Information System (EFFIS) has been developed jointly by the European Commission services (Directorate General Environment and the Joint Research Centre) and the relevant fires services in the countries (forest fires and civil protection services) in response to the needs of European bodies such as the Monitoring and Information Centre of Civil Protection, the European Commission Services and the European Parliament (San-Miguel-Ayanz *et al*., 2013b). EFFIS is a comprehensive system covering the full cycle of forest fire management, from forest fire prevention and preparedness to post-fire damage analysis. The system provides information to over 37 countries in the European and Mediterranean regions, and receives detailed information of forest fire events from 25 countries in the European and Mediterranean regions. It supports forest fire prevention and forest fire fighting in Europe through the provision of timely and reliable information on forest fires (J San-Miguel-Ayanz *et al*., 2012).

2.2. Trend detection procedure

Temporal trends were analyzed for the study period 1985-2009. The observed trends were assessed with the Mann-Kendall test, which is a non-parametric statistical test appropriated to identify trends in time series data (Kendall, 1975; Mann, 1945) and commonly used in environmental research (e.g. Río *et al*., 2011; Todeschini, 2012). Mann-Kendall is a rank non-parametric test that was developed by Mann (1945) and Kendall (1975), and it is suited for detecting linear or non-linear trends (Hisdal *et al*., 2001; Wu *et al*., 2008). In this test, the null (H_0) and alternative hypotheses (H_1) are equal to the nonexistence and existence of a trend in the time series of the observational data, respectively. The magnitude of the change was subsequently assessed by means of the Sen's slope (Sen, 1968), a nonparametric alternative for estimating the median slope joining all possible pairs of observations, which allows the comparison of the magnitude of the detected trends.

The analysis of the number of fires, total burned area and average fire size was carried out at different spatial levels:

- At regional (supranational) level, considering the Euro-Mediterranean region as a whole with the purpose to characterize its fire regimes, known to be markedly different from the rest of Europe. The region under, study shortly referred to as EUMed in what follows, comprises Portugal, Spain, France, Italy and Greece.
- At country level, by analyzing the data of each country individually in order to assess differences between countries that may depend on national settings and policies;
- At province level (NUTS3), to investigate the potential influence of local environmental and socio-economic conditions.

2.3. Uncertainty in trend detection

Temporal trends in number of fires and burned area were assessed using alternative tests for trend detection to determine the variability in the results depending on the trend detection procedure and the robustness of the results obtained with the proposed Mann-Kendall test. As alternative procedures we used two nonparametric tests –Spearman's Rho and Cox-Stuart test– and one parametric test –t-test–. The comparison between the results obtained with the Mann-Kendall test and the alternative procedures was carried out by comparing the resulting positive, negative and non-significant trends through the Cohen's Kappa agreement values.

2.3.1. Spearman's Rho

The Spearman's Rho (SR) test is a simple method, similar to the Mann-Kendall method, with uniform power for linear and non-linear trends. The SR is commonly used to verify the absence of trends (Dahmen and Hall, 1990; Tonkaz *et al.*, 2007). In this test, the null hypothesis (H_0) is that all the data in the time series are independent and identically distributed, while the alternative hypothesis (H_1) is that increasing or decreasing trends exist (Yue *et al.*, 2002).

2.3.2. Cox-Stuart test

Cox-Stuart test (CS Cox and Stuart, 1955) is a sign test based on specific paired comparisons. The CS test is useful for detecting positively or negatively sloping gradual trends in a sequence of independent measurements on a single random variable. The null hypothesis is that no trend exists. If the null hypothesis is accepted, the result indicates that the measurements within the ordered sequence are identically distributed (McCuen, 2003).

2.3.3. T-test

The t-test for trend detection is a parametric method based in the comparison of the means for two different samples (periods). The magnitude of change is measured by the difference in sample means between the two periods. Parametric tests assume that the random variable is normally distributed and homogeneous variance. The t-test for trend detection is based on linear regression, and therefore checks only for a linear trend.

3. Results

3.1. Trends in number of fires

The general trend for the whole study area (EUMed) is an increase in the number of fires, even though annual fluctuations are evident along the period (Figure1). In the 90's a substantial increase was observed, partly due to the changes in the reporting systems in the countries that occurred during this time, mostly driven by EC regulations. Other reasons for the rise in the number of fires during this period may be associated with fuel accumulation related to land cover changes such as expansion of shrublands or abandonment of agricultural lands (Carmo *et al*., 2011; Lloret *et al*., 2002; Romero-Calcerrada *et al*., 2008).

The results of the Mann-Kendall test show that, for the entire study period, the general trend is an increase, although not significant (S=64, p=0.14).

However, the downscaling of the analysis at national and province (NUTS3) levels reveals the existence of certain spatial variation in the trends concerning the number of fires. At country level, Portugal, Spain and Greece show an increasing trend in the number of fires for the whole study period, while France and Italy present a general decrease (Table 1). It is noticeable that the increasing trend observed for Portugal and the decreasing trend of Italy, are significant.

Table 1. Results of the Mann-Kendall test and Sen's slope for the number of fires by country (grey-shaded, significant trends).

	Portugal	**Spain**	**France**	**Italy**	**Greece**	**EUMed**
Mann-Kendall score (S)	110	82	-28	-164	22	64
p value	0.01	0.06	0.53	0.01	0.62	0.14
Sen's slope	801.9	396.9	-33.04	-346.2	5.969	713.4

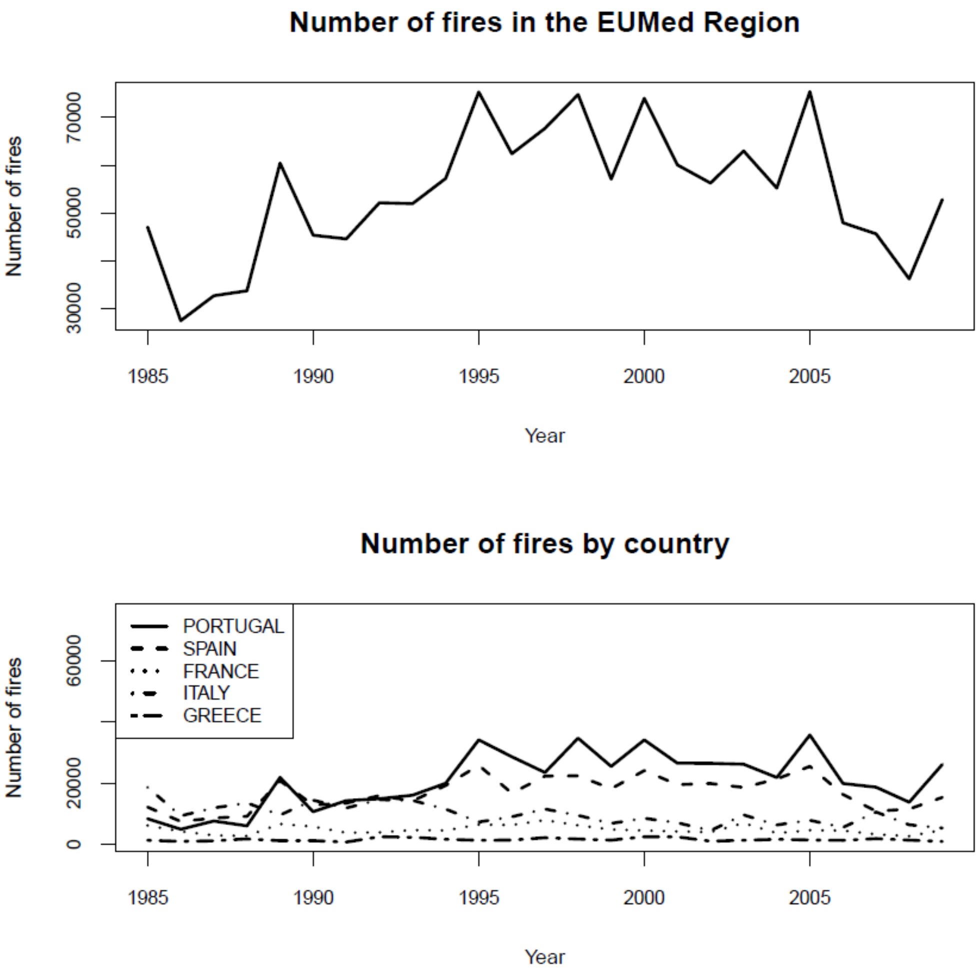


Figure 1. Total annual number of fires in the EUMed region from 1985 until 2009.

Although not significant, the increasing trend in the number of fires for the whole EUMed region is highly correlated with the observed trends in Portugal and Spain (Table 2) according to the MIC correlation index (Reshef *et al*., 2011).

Table 2. EUMed-Country correlation values for number of fires.

	Portugal	Spain	France	Italy	Greece
MIC	0.85	0.99	0.46	0.48	0.28

At NUTS3 level (Figure 2), the trend in the number of fires shows large variability, although general patterns for most provinces can be observed by country. Portugal and Spain have the majority of provinces with a significant increasing trend, while Italy and Greece have more provinces with a significant decreasing trend. In the case of Italy, an exception occurs in Sicily, which shows a significant increasing trend, while all the other provinces show a decreasing trend or no trend. In France, most of the provinces with available data indicate no trend or a decreasing trend. However it should be noted that, after 1998, the data in Greece at NUTS3 level are not complete, because of changes in the reporting system in the country.

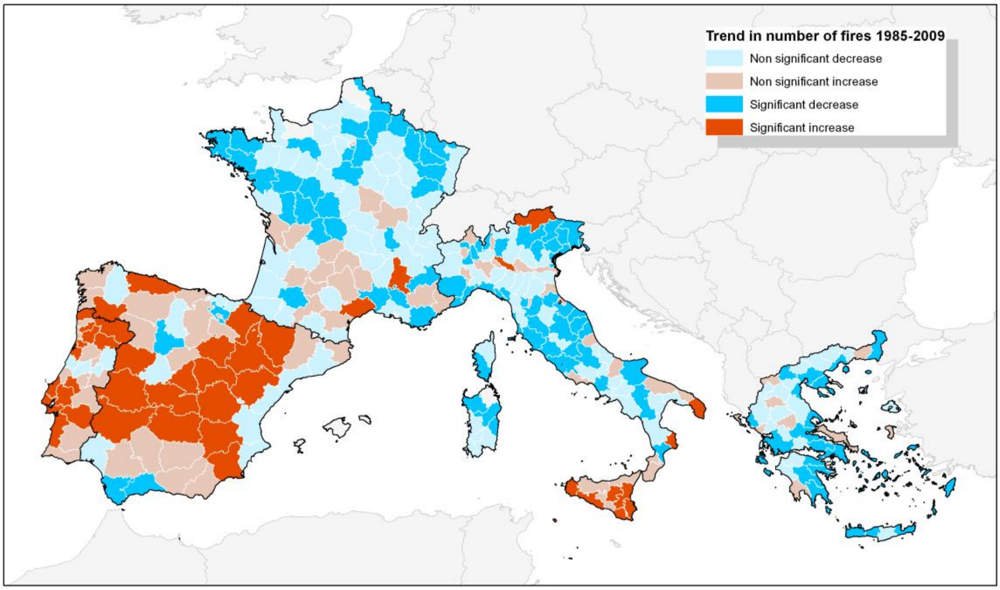


Figure 2. Trend in number of fires by province in the EUMed region between 1985-2009, obtained from the Mann-Kendall test.

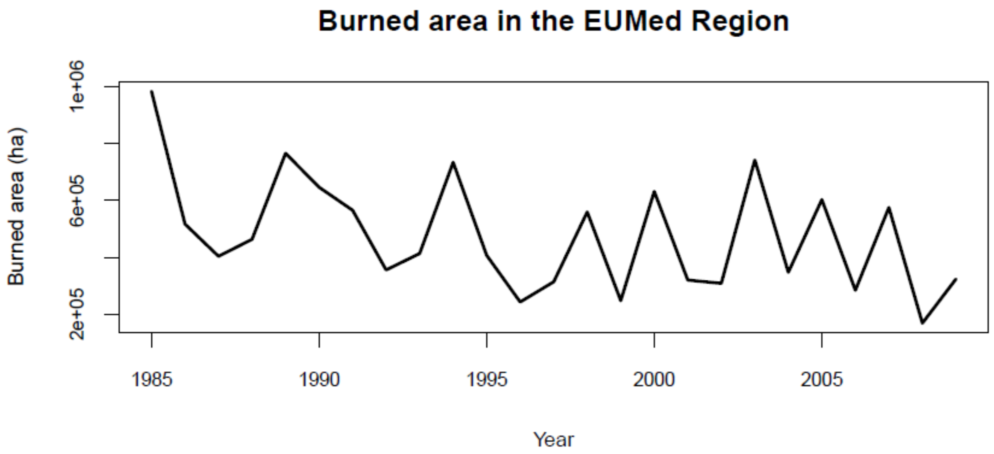
Table 3. Results of the Mann-Kendall test and Sen's slope for the burned area by country (grey-shaded, significant trends).

	Portugal	Spain	France	Italy	Greece	EUMed
Mann-Kendall score (S)	-6	-100	-52	-96	-68	-25
p value	0.90	0.02	0.23	0.03	0.12	0.03
Sen's slope	-101.6	-5175	-473.5	-3243	-1703	-3197

3.2. Trends in burned area

As opposed to the number of fires, the burned area in the EUMed region shows a decreasing trend since 1980 with strong annual fluctuations (Figure 3). The results of the Mann-Kendall test show that the general trend is a decrease of the burned area at both national and supranational levels (Table

3). However, the decreasing trend was only significant for the whole EUMed region, Spain and Italy. They show a higher score and a median annual decrease in area burned of 5175 ha for Spain and 3243 ha for Italy, according to the Sen slope.



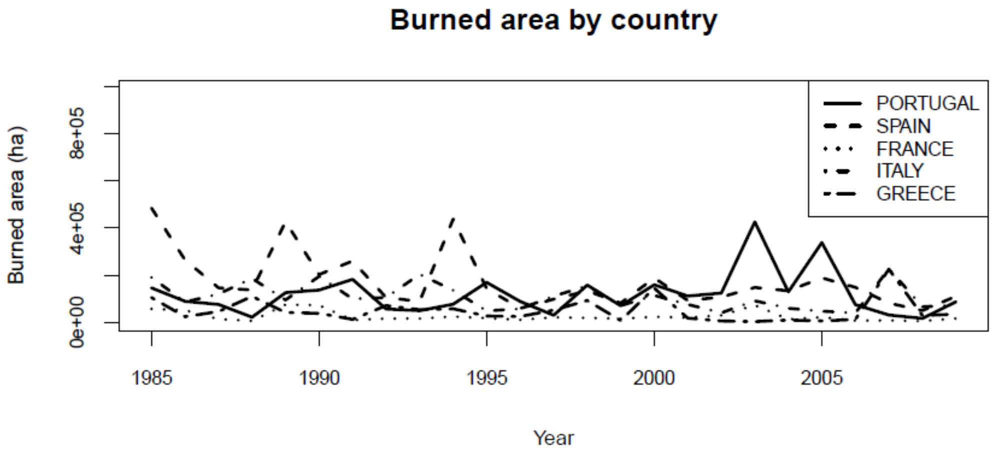


Figure 3. Total annual burned area in the EUMed region from 1985 until 2009.

This decrease in total burnt area is likely related to the improvement in fire detection and fire-fighting techniques verified in the last years. It must be noted that, for the whole EUMed region there are contradictory tendencies, with an increasing number of fires that is accompanied by a decreasing area burnt by these fires. However, unlike with the number of fires, trends in burned area at supranational scale do not seem to be correlated with country values (Table 4).

Table 4. EUMed-Country correlation values for burned area.

	Portugal	Spain	France	Italy	Greece
MIC	0.39	0.50	0.58	0.50	0.30

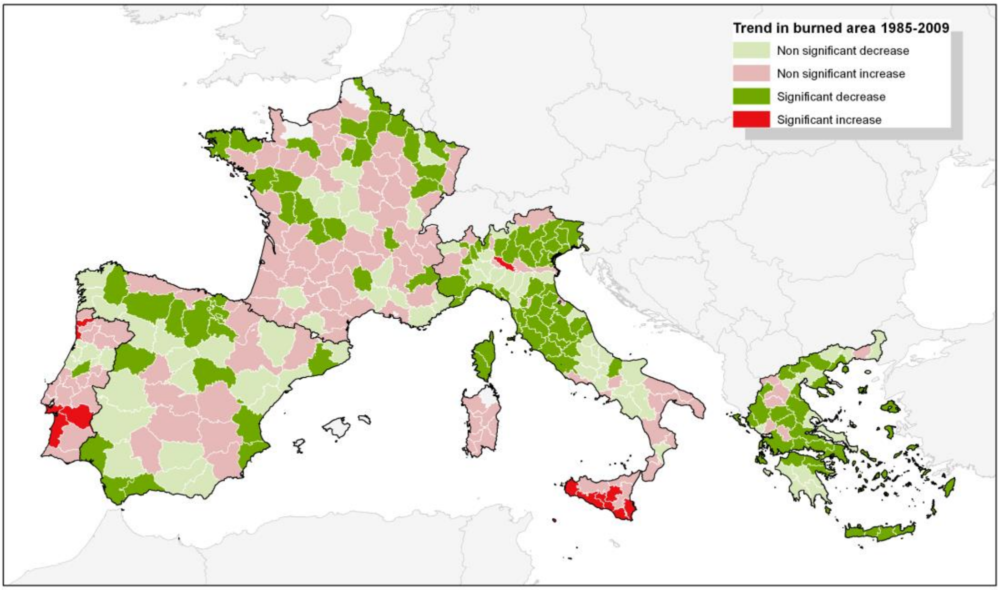


Figure 4. Trend in the burned area by province in the EUMed region between 1985-2009, obtained from the Mann-Kendall test.

At NUTS3 level, the burned area evidences a general significant decreasing trend for the provinces of all countries, except Portugal and the region of Sicily in Italy, between 1985 and 2009.

3.3. Trend detection uncertainty

According to the results summarized in Tables 5 and 6, there is more uncertainty in trend detection for burned area than for number of fires. According to these results, the trend analysis of burned area should be carefully analyzed.

Table 5. Cohen's Kappa agreement values between Mann-Kendall test and the alternative trend detection procedures.

	SP	CS	T-test
N. Fires	0.9	0.7	0.7
B. Area	0.9	0.2	0.5

Table 6. Trend detection comparison by cross-tabulation.

N. Fires	SR		
Kendall	Dec. Trend	No trend	Inc. Trend
Dec. Trend	96	6	0
No trend	8	169	4
Inc. Trend	0	0	44

N.Fires	CS		
Kendall	Dec. Trend	No trend	Inc. Trend
Dec. Trend	77	25	0
No trend	20	161	0
Inc. Trend	0	17	27

N.Fires	T-test		
Kendall	Dec. Trend	No trend	Inc. Trend
Dec. Trend	80	22	0
No trend	14	166	0
Inc. Trend	0	13	31

B. Area	SR		
Kendall	Dec. Trend	No trend	Inc. Trend
Dec. Trend	112	3	0
No trend	8	188	3
Inc. Trend	0	1	10

B. Area	CS		
Kendall	Dec. Trend	No trend	Inc. Trend
Dec. Trend	38	77	0
No trend	43	155	1
Inc. Trend	0	6	5

B. Area	T-test		
Kendall	Dec. Trend	No trend	Inc. Trend
Dec. Trend	53	62	0
No trend	5	193	1
Inc. Trend	0	7	4

When looking into the comparison between the proposed tests, the highest agreement is found among Mann-Kendall and SR, for both the number of fires and the burned area. On the other hand, the CS test shows the lowest agreement, although, in the case of the number of fires, it presents a moderate Kappa value of 0.7.

4. Discussion

According to our results, forest fires have increased significantly in the EUMed Region during the last 25 years, especially in Portugal, Spain and the region of Sicilia in the south of Italy. This increase in fire outbreaks may be related to several reasons such as the traditional usage of fire in agricultural and cattle raising practices in the region (Bowman *et al*., 2011), to demographic changes related to the abandonment of rural areas, and to fuel accumulation due to the lack of forest management practices in the region, as these practices are often non-profitable (Jesús San-Miguel-Ayanz *et al*., 2012). As in most human-dominated landscapes where anthropogenic ignitions surpass natural ignitions (San-Miguel Ayanz and Camia, 2009), in the EUMed Region, population density is strongly related to fire ignition (Bar Massada *et al*., 2012). Although, overall, the rural population in Southern Europe has decreased, peaks of high population density in recreational wildland areas during holiday periods lead to increased fire ignition due to the increase of human pressure on wildlands (Jesús San-Miguel-Ayanz *et al*., 2012). This effect is further exacerbated by the expansion of urban areas into wildland areas, due to either the expansion of cities or the construction of secondary houses in rural areas, leading to an extended Wildland Urban Interface (WUI) in the region (Galiana-Martin *et al*., 2011). Furthermore, the difficult fire management of the extensive WUI in Southern Europe contributes to fire incidence and can lead to catastrophic fires (San-Miguel-Ayanz *et al*., 2013a).

On the other hand, despite the generalized increase observed in number of fires, a decreasing trend in the annual burned area has been detected at all the analysis scales. This implies that the average fire size is decreasing possibly due to the efforts made to achieve a better management of wildfires during the last decades. However, according to the results obtained in section 3.3, certain uncertainty exists regarding the trend detection for burned area and thus, further analysis should be carried out to ascertain this phenomenon.

5. Conclusions

Forest fire events have significantly increased in the EUMed Region during the last 25 years, whereas the annual burned area presents a reverse behavior, with a generalized decrease in the period 1980-2009. Particularly, Portugal, Spain and the area of Sicilia in the south of Italy, appear as the regions with the highest fire impact, since they present both increasing number of fires and burned areas. However, there is a significant spatial variation in the detected trends. The provinces with a high increase in both number of fires and burned area were located in Portugal and Southern Sicily, while decreasing trends in both variables were found mostly in the northern provinces of Spain and Central Greece. The majority of the provinces of Italy and Greece showed no trend. The variation in the number of fires and burned areas between countries and provinces is potentially related to the influence of physical parameters like topography, fuel amount and condition and weather, which vary spatially and/or seasonally. Additionally, the number of fires is also related to the diversity of the environmental and socio-economic conditions found throughout the study area, which set the availability of ignition agents.

However, the fire recording process, which is different in each country, and in some cases even in each NUTS2 region (Spain) and which has been improved through time, can also have influence in the fire datasets, especially in the number of fires, and in consequence in the results. Despite some level of uncertainty, our results show conclusively that the general behavior of the detected trends in the EUMed region is a decrease in the total burned area and an increase in the total number of fires the region.

Acknowledgments

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CHAPTER 6. NEW METHODOLOGICAL APPROACHES TO MODEL HUMAN CAUSALITY IN FOREST FIRES

This chapter presents the results, discussion and main conclusions obtained from the application of different spatial explicit methods, techniques and algorithms for modeling historical human-caused forest fires at national scale.

On one hand, machine learning and GWR methods have been explored and compared to traditional regression methods in order to test their performance as a tool for spatial modeling of human-caused fire occurrence.

On the other hand, GWR techniques have also provided deep insights into wildfires and its driving factors, not only as a stationary phenomenon but also as a spatial-varying process.

Modeling the spatial variation of the explanatory factors of human-caused wildfires in spain using geographically weighted logistic regression

(Appendix D)

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Abstract

Forest fires are one of the main factors transforming landscapes and natural environments in a wide variety of ecosystems. The impacts of fire occur both on a global scale, with increasing emissions of greenhouse gases, and on a local scale, with land degradation, biodiversity loss, property damage, and loss of human lives. Improvements and innovations in fire risk assessment contribute to reducing these impacts. This study analyzes the spatial variation in the explanatory factors of human-caused wildfires in continental Spain using logistic regression techniques within the framework of geographically weighted regression models (GWR). GWR methods are used to model the varying spatial relationships between human-caused wildfires and their explanatory variables. Our results suggest that high fire occurrence rates are mainly linked to wildland-agricultural interfaces and wildland-urban interfaces. The mapping of explanatory factors also evidences the importance of other variables of linear deployment such as power lines, railroads, and forestry tracks. Finally, the GWLR model gives an improved calculation of the probabilities of wildfire occurrence, both in terms of accuracy and goodness of fit, compared to global regression models.

Keywords: fire risk; human causality; forest fires; GWR; logistic regression; GIS modeling.

1. Introduction

Forest fires are an important factor in landscape transformation, vegetation succession, land degradation, and air quality. Although fire has been traditionally used as a land management tool, and many ecosystems are well adapted to fire cycles, recent changes in weather and social factors relating to wildfire could be modifying the historical fire regimes (González *et al*., 2010; San-Miguel-Ayanz *et al*., 2012), possibly resulting in undesired effects. Indeed, the influence of climate change on an increase in fire frequency and intensity has been reported in several ecosystems (Kasischke and Turetsky, 2006; Westerling *et al*., 2006). Climatic projections suggest worse conditions in future decades in tropical and boreal regions (Flannigan *et al*., 2005). In addition to these global effects, wildfires also have relevant local effects which are commonly associated with the frequency and intensity of fires, often implying soil loss and land degradation, loss of lives or biodiversity, and damage to property and infrastructure (Omi, 2005). On the other hand, human beings have a great impact on fire regimes because they alter ignition frequency and fuel fragmentation and suppress fires (Guyette *et al*., 2002). The dynamics of fire regimes in southern Europe are mainly related to human factors. In fact, humans are responsible for more than 95% of the fires in this region (San-Miguel Ayanz and Camia, 2009). In the case of Spain, nearly 90% of wildfires are related to an anthropogenic source (Chuvieco *et al*., 2014; Martínez *et al*., 2009). It is thus clear that human factors play an important role in fire ignition. Furthermore, determining the explanatory factors facilitates the development of future wildfire scenarios in the context of climate change. Therefore, a better comprehension of the local driving forces of fire ignition and of predicting where fires are likely to start are core elements in designing strategies to mitigate wildfire initiation and to identify areas at risk (Finney, 2005). In recent years, several methods for wildfire risk assessment have been developed using different methodological schemes, variables, and scales (Martínez-Vega *et al*., 2012). Without being exhaustive, some of the more recent efforts have included those by Amatulli *et al*. (2006), Chuvieco *et al*. (2012, 2010), Cooke *et al*. (2007), Loboda (2009), Martínez *et al*. (2009,2011), Martínez and Koutsias (2013), Padilla and Vega-García (2011), and Romero-Calcerrada *et al*. (2010). Similar efforts have been invested in modeling fire occurrence (see Plucinsky (2011) for an exhaustive review) and, particularly, to human-caused ignition (Martínez *et al*. 2009,2011,2013; Padilla and Vega-García, 2011). The analysis of human factors in forest fires is widely recognized as critical for fire risk estimation (Kalabokidis *et al*., 2002; Martínez *et al*., 2004b), however the literature on this topic is scarce and mainly site-specific (Le Page *et al*., 2010; Martínez *et al*., 2009) perhaps due to the complexity of predicting human behavior, both in space and time. Currently, most fire risk models in use are based on physical parameters such as weather data or fuel moisture content – there is no global forest fire risk system that includes the human factors operationally, although some consider it in their components (San-Miguel Ayanz and Camia, 2009). However, over recent years, the role of human factors in fire behavior modeling has been increasing, and several models now include an anthropogenic component in their assessments (Chuvieco *et al*., 2014, 2010; Loepfe *et al*., 2011).

Additionally, the fit of statistical models of risk estimation, previously discussed for different regions of the Iberian Peninsula by Chuvieco *et al*. (2010), shows that the explanatory factors vary spatially in their significance and contribution. This finding is also supported by Padilla and Vega-Garcia (2011), who reported the existence of high spatial variation in the relationships between explanatory variables and historical human-caused fire occurrences. Accordingly, the use of global regression methods over wide areas, such as here, could be inappropriate due to the application of stationary coefficients over the whole study area, possibly masking local interactions with the explanatory factors. Hence, to better understand the causes of wildfires, the spatial variation of the human factors associated with wildfires must be properly analyzed. To overcome this limitation, in the present paper we use geographically weighted regression techniques (GWR (Fotheringham *et al*., 2002), which allow us to incorporate in the models the spatial variation of the explanatory variables, in a way similar to Martínez and Koutsias (2013) but focusing exclusively in the human influence on wildfire ignitions. Examples of the application of GWR to a number of subjects are found in Cardozo *et al*. (2012), Chalkias *et al*. (2013), Chi *et al*. (2013), Li *et al*. (2011), Lu *et al*. (2011), Tu (2011), Su and Zhang (2012), Wang *et al*. (2013) and Xiao *et al*. (2013); GWR is applied specifically to the occurrence of forest fires in Chuvieco *et al*. (2012), Koutsias *et al*. (2005), Martínez and Koutsias (2011), Martínez *et al*. (2013), and Rodrigues and de la Riva (2012). In this context, we apply binary logistic regression, commonly used for probabilistic explanation of human-caused occurrence (Chuvieco *et al*., 2010; Martínez *et al*., 2004b; Vasconcelos *et al*., 2001; Vega-Garcia *et al*., 1995), but within the framework of GWR models.

Therefore, the aim of this paper was to model and analyze, using GWLR techniques, the spatial variation in the human factors associated with forest fires. Our hypothesis is that the explanatory factors for human wildfires are not-stationary, rather their relationship with fires changes significantly over the space. The fit of GWLR models (geographically weighted logistic regression) required the statistical analysis and spatialization both of the historical occurrence (in the period 1988-2007) and of a large number of explanatory variables, selected based on experience of models at regional and national scales (Chuvieco *et al*., 2010; Martínez *et al*., 2009; Vilar del Hoyo *et al*., 2008). Ignition data was retrieved from the General Statistics of Wildfires database (EGIF), one of the oldest 'complete' wildfire databases in Europe, beginning in 1968 (Vélez, 2001). The EGIF database registers information about several parameters related with fire ignition such as location, cause, date, size or affected vegetation. The explanatory variables were derived from spatial datasets and statistical data obtained from official data sources of the

Spanish Government, later explained in detail. Model adjustment was carried out using a random sample of 60% of the ignition data, reserving the remaining 40% for the validation process. Additionally, an alternative validation sample constructed from the occurrence in the period 2008-2011 was used in the validation process to test the predictive capacity of the model.

This work was developed within the framework of the FIREGLOBE project (www.fireglobe.es, Chuvieco *et al.*, 2014, 2011). In following sections, we describe the method used for modeling the spatial variation of the explanatory factors, the main results of the application of the methodology to peninsular Spain, the degree of fit of the model, and the results of the validation process. A comparison of the performance of GWR and global models, and of our work and similar studies is also conducted. Finally, we present our conclusions and suggestions for further research.

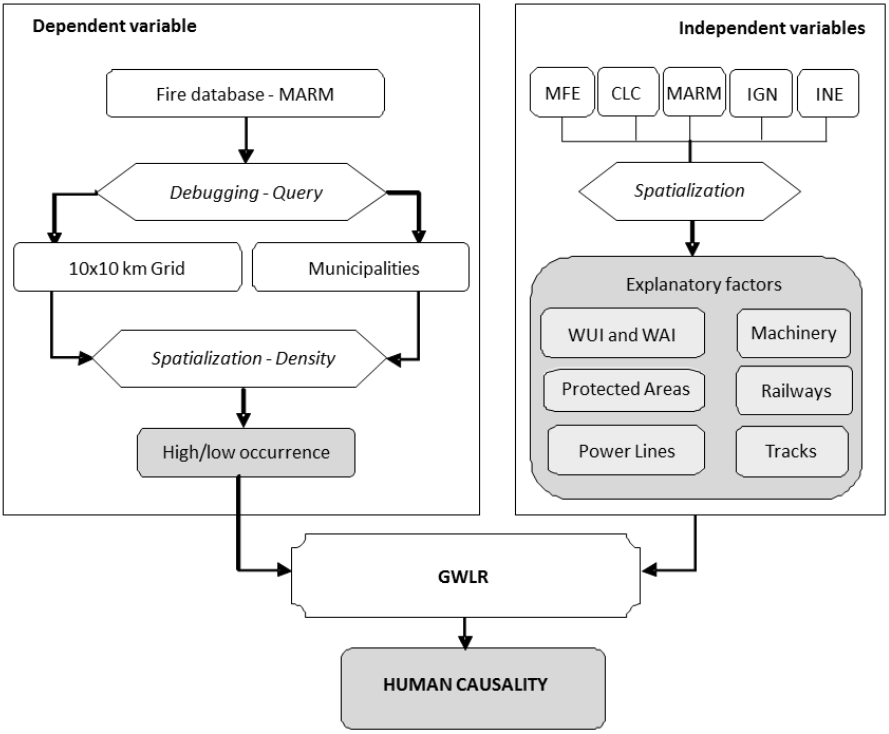

Figure 1. Workflow followed for human causality modeling.

2. Materials and methods

The methodology for modeling human causality in forest fires is based on GWLR techniques. Specifically, we used the GWR 3.0 software developed by the NCG (Fotheringham *et al.*, 2002). Like global logistic regression models (GLR), GWLR are statistical models that provide insights into the relationship between a qualitative dependent variable, dichotomous in our case, and one or more independent explanatory variables, whether qualitative or quantitative. Therefore, its development requires on the one hand a binary dependent variable, in this case the high/low occurrence of fires, and secondly a set of predictor variables, which are listed below. Figure 1 shows a schematic of the workflow followed for modeling human causality.

2.1. Overview of GWLR

GWR techniques extend the traditional use of global regression models, allowing calculation of local regression parameters. Taking as a starting point the typical equation of the logistic regression:

$$y_i = \frac{e^{(\beta_0+\beta_1 x_{1i}+\ldots+\beta_k x_{ki})}}{1+e^{(\beta_0+\beta_1 x_{1i}+\ldots+\beta_k x_{ki})}} \qquad (1)$$

the mathematical expression of its geographically weighted version is:

$$y_{(u_i,v_i)} = \frac{e^{(\beta_0(u_i,v_i)+\beta_1(u_i,v_i)x_{1i}+\ldots+\beta_k(u_{ki},v_{ki})x_{ki})}}{1+e^{(\beta_0(u_i,v_i)+\beta_1(u_i,v_i)x_{1i}+\ldots+\beta_k(u_{ki},v_{ki})x_{ki})}} \qquad (2)$$

where (*ui*,*vi*) are the location coordinates in space of point *i*.

Accordingly, the use of GWLR models allows one to obtain regression coefficients whose values vary spatially, thus obtaining a different set of regression coefficients for each location in the study area. To do this, a regression model is adjusted for each point and its nearest neighbors. The influence of the points in this neighborhood varies according to the distance to the central point (Fotheringham *et al*., 2002). The optimum distance threshold (also known as the bandwidth) or the optimum number of neighbors is determined in two ways: by minimizing the square of the residuals (Cross-Validation, Cleveland, 1979) or by minimizing the Akaike Information Criterion (AIC, adapted for GWR by Hurvich *et al*., 1998).

In addition to the regression coefficients, the GWLR model calculates several useful statistical parameters to analyze each of the explanatory variables, such as the value of the Student t test (used to determine the level of significance) and the local R^2 value (i.e., the R^2 value of the resulting model at the point where the value is referenced and its neighbors), among others. However, GWLR does not allow estimation of regression coefficients in locations where there is no observation. In order to overcome this limitation and apply the model to the entire area of study, the regression coefficients are interpolated using the Local Polynomial Interpolation method in ArcGIS 10.1 (1st order polynomial and exponential kernel function), thus preserving the original values of locations with observations and hence the internal consistency of the model.

In this work, a GWLR model was adjusted using a random sample of 60% (3582 points) of the total sample, reserving the remaining 40% (2408 points) for the validation process. Model calibration was carried out using Adaptive Kernel to select the bandwidth, optimized according to the value of AIC. In this case, the optimum number of neighbors was 914.

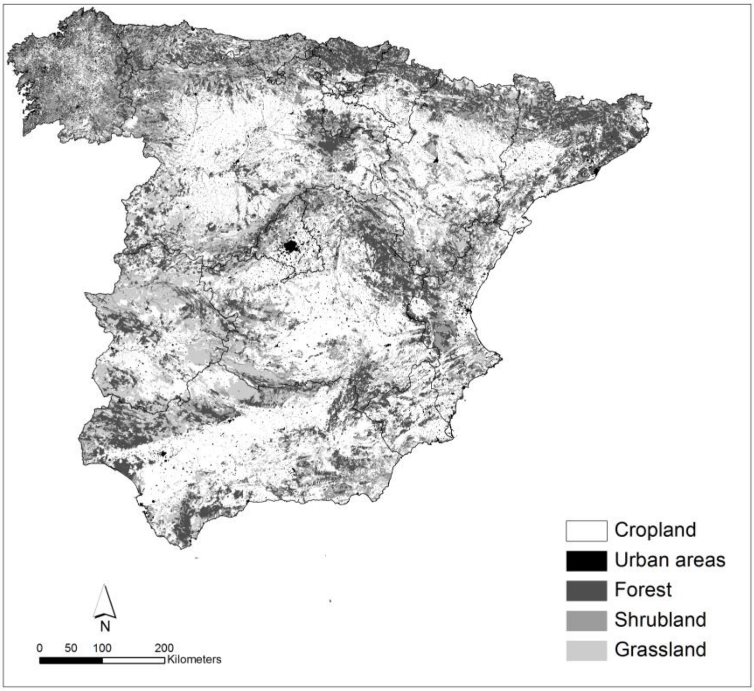

Figure 2. Study area and land use distribution.

2.2 Study area

The study area covers the whole of peninsular Spain excluding the Balearic and Canary Islands and the autonomous cities of Ceuta and Melilla, as some parameters needed to develop the methodology were not available in those areas. Thus the total area of the study region was around 498 000 km^2. Further, the study region was restricted to forested areas; consequently, urban areas and agricultural and inland water zones were excluded from the assessment and no data are detailed or shown on the maps (Figure 2). Spain is very biophysically diverse, presenting a wide variety of climatic, topographic, and environmental conditions. This diversity also appears when discussing socioeconomic conditions, in terms of population systems and population structure, productive sector, or territory structure. The complexity of the socioeconomic conditions thus plays a determinant role, which is especially important when modeling human factors, since this complexity is transferred to the relationships between socioeconomic variables and a natural phenomenon such as wildfires, making assessment less straightforward.

2.3 Dependent variable

The dependent variable was created on a conceptual framework which assumed that there were no true cases of fire absence. In ignition data, most or all of the fire occurrences are accounted for, which may make it seem as if all other locations in the landscape have no fires. In this context, most previous attempts at fire occurrence modeling had used background subsets of "no occurrence" during the analyzed time span, considering them to be true cases of fire absence (e.g., Chuvieco *et al.*, 2010; Padilla and Vega-García, 2011). However, the fact that these areas did not experience an ignition event during the temporal span of the data set does not mean that they could not feasibly support an ignition event in the future, or that they never ignited in the past (Bar Massada *et al.*, 2012). In line with this reasoning, the dependent variable – high/low wildfire occurrence – is constructed from the EGIF database, 1988-2007, compiled by the Ministry of Environment, Rural, and Marine Affairs (MARM) using forest fire reports from the various autonomous regions (Moreno *et al.*, 2011). Among other useful information relating to fire events, these reports include data regarding the starting location point of each fire. This position is recorded on the basis of a reference 10x10km grid, used by firefighting services for approximate location of fire events, and the municipality origin of the ignition. The ignition location procedure is based in the method developed by de la Riva *et al*. (2004). This method is widely recognized and has been used in many wildfire assessment research works in the Spanish territory such as Amatulli *et al*. (2007) or Chuvieco *et al*. (2010). The method proposes a multi-step procedure which successively refines and decreases the potential location area of the ignition points. Firstly it starts in the 10x10 grid with a potential location area of 100 km2. Then this area is decreased by intersecting with the municipality boundaries. Finally, the location area is restricted to the forest perimeter – since the ignition location of every wildfire is expected to be in the forest area – to determine the final potential location area. This process leads to a significantly smaller area where the ignition points are then randomly distributed. After cleaning and treatment of the database, human-caused fires over 5 ha in size were selected (8727 fires) and spatialized by the random assignment of each fire to its respective combination of grid/municipality, restricted to forested areas. This allowed us to calculate fire density maps with a spatial resolution of 1x1 km by overlapping the ignition points cloud and a 1x1km UTM grid (which perfectly fits the 10x10 grid). It should be noted that in this study density values were calculated only in locations where at least one fire event was recorded (7873 cells). These density values were divided into high (1) and low occurrence (0) by separating the sample into tertiles. We considered the third tertile (sample above the 66th percentile or 1.83 fires/km^2) as high occurrence, and the first tertile (sample below the 33th percentile or 1.00 fires/km^2) as low occurrence, discarding the second tertile from the analysis.

2.4 Independent variables

As stated previously, the explanatory variables were selected on the basis of experience of models at regional and national scale (Chuvieco *et al*., 2010; Martínez *et al*., 2009; Vilar del Hoyo *et al*., 2008). Thus, the explanatory variables were classified according to the typology of the affecting factor (Leone *et al*., 2003; Martínez *et al*., 2004a), as follows:

1. Factors related to socioeconomic transformation.
    - 1.1. Abandonment of traditional activities in wildland/rural areas. Accumulation of forest fuel.
        - 1.1.1. ***People employed in the primary sector***. Obtained at the municipal level from the Agricultural Census 1999 of the Spanish Statistics Institute (INE).
    - 1.2. Abandonment of traditional activities in wildland/rural areas especially in privately owned forests with no prospect of economic profit. Little or no interest in forest conservation.
        - 1.2.1. ***Forestry area in public utility***. Delimitation of the area occupied by forestry areas included in the public utility catalog.
    - 1.3. Increasing use of forest as a recreational resource. More frequent visits to forests.
        - 1.3.1. ***Tracks***. Area occupied by the buffer 200 meters either side of the forestry track network. Obtained from BCN200.
    - 1.4. Human presence, population increase and urban growth. Increased pressure on wildlands
        - 1.4.1. ***Wildland-Urban Interface (WUI)***. Area occupied by the buffer 200 meters from the line of contact to the forest area. Constructed from the Spanish Forestry Map 1:200000 (MFE200).

1.4.2. ***Changes in demographic*** *potential*, *1991-2006* (Calvo and Pueyo, 2008). Variation rate between the demographic potential in 1991 and 2006.

2. Factors related to traditional economic activities in rural areas.
   2.1. Aged rural population. Traditional management methods.
      2.1.1. ***Percentage of owners of holdings aged over 55 years.*** Obtained at the municipal level from the Agricultural Census 1999 of the Spanish Statistics Institute (INE).
   2.2. Agriculture. Use of fire to clear harvesting waste, cleaning along borders of cropland.
      2.2.1. ***Wildland-agricultural interface (WAI)***. Area occupied by the buffer 200 meters from the line of contact to the forest area. Constructed from the Spanish Forestry Map 1:200000 (MFE200).
   2.3. Cattle grazing. Possible fire to maintain herbaceous vegetation.
      2.3.1. ***Extensive livestock***. Obtained at municipal level from the Agricultural Census 1999 of the Spanish Statistics Institute (INE).
      2.3.2. ***Wildland-grassland interface (WGI)***. Area occupied by the buffer 200 meters from the line of contact to the forest area. Constructed from the Spanish Forestry Map 1:200000 (MFE200).

3. Factors that could cause fire mainly by accident or negligence.
   3.1. Electric lines. Possible cause of ignition by accident.
      3.1.1. ***Power lines***. Area occupied by the buffer 50 meters either side of the high, medium, and low voltage power network. Obtained from BCN200.
   3.2. Engines and machines working in or close to forested areas Possible cause of ignition by accident or negligence.
      3.2.1. ***Density of agricultural machinery (DAM).*** Obtained at municipal level from the Agricultural Census 1999 of the Spanish Statistics Institute (INE).
   3.3. Existence of roads, railroads, tracks, and accessibility. Greater human pressure on wildland.
      3.3.1. ***Railroads***. Area occupied by the buffer 200 meters either side of the railroad network (excluding the high-speed network). Obtained from a digital cartographic database (BCN200).
      3.3.2. ***Tracks***.
      3.3.3. ***Changes in demographic potential 1991-2006***

4. Factors that could help prevent fires.
    4.1. Protected area. Increasing concern about forest protection.
        4.1.1. ***Protected areas***. Delimitation of the area occupied by protected natural areas and the *Natura 2000* network.
5. Factors that generate conflicts, and which could lead to intentional starting of fire and/or facilitating its spread.
    5.1. Changes from forest use. Possible cause of arson.
        5.1.1. ***Changes in land cover***. Loss or increase of area covered by forest or semi-natural regions. Obtained from the Corine Land Cover 1990 and 2006 maps.
    5.2. Fire industry. Fire started to gain income, work, payment or subsidies from fire prevention or fighting and in restoration of land affected by fire.
        5.2.1. ***Unemployment rate***. Obtained for municipal level in 2007 from the population and housing census 2001 (updated to 2007) of the Spanish Statistics Institute (INE).

All the predictive variables, as well as the dependent variable, were spatialized at a resolution of 1x1 km (see Figure 3). To ensure consistency of results, we conducted an analysis of collinearity in the explanatory variables using the non-parametric Spearman's Rho correlation index. No collinear variables were found (Table 1). To determine the variables that would eventually be included in the model, we set a preliminary GWLR model including all the considered variables. From this first model, we discarded those variables that were not significant by Student's t test ($p<0.05$), or its explanatory sense was not consistent with what would be expected based on experience and expert opinion. The variables used for adjustment of the final model were WAI, WUI, protected areas, power lines, railroads, tracks, and DAM.

2.5 Model validation

The model validation procedure was conducted using firstly the local R^2 values obtained during the calibration of the model. The local R^2 values allow a first assessment of the degree of fit of the GWLR model. Secondly, we present the percentage of success in the classification of the points and the calculation of the degree of agreement using Cohen's Kappa. The Kappa value is calculated for two different validation samples: the first with 40% of the total sample for 1988-2007 and the second constructed from the fire events recorded for 2008-2011, to test the predictive capacity of the model. The latter was spatialized using the same process and thresholds for the classification of the occurrence as for the period 1988-2007.

3. Results and discussion

The main results obtained from modeling human causality in forest fires were the regression coefficients of the explanatory variables, the spatial variation in the significance level of these variables, and the probability of wildfire occurrence. The results of the validation are also presented in this section.

3.1 Spatial variation of probability of ignition and its driving factors

Figure 4 shows the map of interpolated regression coefficients associated with the explanatory variables. As can be seen, the values of these coefficients vary spatially as a result of the adjustment by GWLR. At this point, it should be noted that these values are not directly related to a greater or lesser weight in the model but to the units of measurement of the predictive variables. However, the maps of regression coefficients are a first approximation to the measurement of the spatial variation of the explanatory factors. To determine the degree of participation of the variables in the model, the significance thresholds should be taken as reference, mapped in Figure 5. These thresholds are not only linked to the degree of participation of the independent variables in the model, but also provide information about their explanatory sense. Accordingly, the higher the significance threshold (and therefore the higher the value of the Student t test, regardless of its sign), the greater the participation of the variable in the model. On the other hand, positive values of significance imply a direct relationship between the explanatory variable and human causality or, which is the same, the higher the value of the variable the higher the probability of occurrence, and vice versa. In the opposite case, i.e., Student t values below 0, we find an inverse relationship between the values of the explanatory variables and the occurrence, the probability being lower the greater the value of the variable. For a correct interpretation of these results, it is important to recall that the mapped values of significance thresholds represent a value obtained locally with a sample composed of the point where the value is assigned and represented on the map, plus its 914 closest neighbors, and not only at the represented point.

A more detailed analysis of the cartography, shown in Figure 6, reveals that the greatest burden in the model falls on the explanatory variable WAI. Contrary to the other variables, which do not exceed the threshold of $p<0.25$ in some parts of the study region, WAI is significant with $p<0.05$ in almost all locations which means that it has a relevant contribution in the whole Spanish territory. To this must be added the fact that the explanatory sense of the WAI is always positive. This outstanding contribution could be related to the large-scale socioeconomic changes in recent decades which have driven shifts in the structure of Spanish rural landscape, increasing the complexity of the spatial distribution of the WAI and, accordingly, increasing wildfire frequency. It should also be noted that the WAI is an area of intense competition between agricultural and forestry activities. In some cases this competence may turn into conflicts of interest that result in aggressive practices such as the use of fire for clearing forests and pasture establishment. This, jointly with the scarcity of forestry works, makes WAI areas an important source of forest fire occurrence (Ortega *et al*., 2012). Also noteworthy is the contribution to the explanation of the occurrence of the WUI, which plays an important role in the sites located in the imaginary triangle formed by the center of the Iberian Peninsula (Madrid) and the Mediterranean coast (especially the stretch Valencia–Barcelona). The intense growth of urban areas can be considered a general trend nationwide, but it has been particularly intense in this area, leading to an increased human pressure on wildlands. In addition, the WUI are regions marked by their highly scattered system of settlements, a situation that is a potential source of wildfire ignition particularly in those areas with the highest levels of urbanization. That is the case of the metropolitan rings of Madrid, Barcelona and, to a lesser extent, Valencia and the rest of Mediterranean coast, due to the higher intensity of touristic uses (Galiana-Martín, 2012). Then, in order of highest significance, the linear variables appear corresponding to the communication network and accessibility (railroads, power lines, and forest tracks). The railroads, like the WAI, have a positive explanatory sense in all locations though the regression coefficients seem not to vary over the study area. In the case of power lines and forest tracks, although most of their locations are not significant (with $p<0.25$), they also have a positive explanatory sense. DAM is expected to have a positive explanatory sense in all locations of the sample, but appears with a negative sign in the northwest area corresponding to Cantabria and Galicia. Finally, the protected areas participate in the model as a deterrent agent, lowering the fire occurrence in most of the country, and occurring with a positive sign only in some locations of the northwestern peninsula. In addition to the significance thresholds, Figure 4 also shows the mapping of the number of significant variables with $p<0.05$. As can be seen, there is always at least one significant variable in the threshold, and it is most common to find two or more significant variables.

Finally, we present the probability map of occurrence relating to human causality (Figure 6). Based on this figure, the highest values of probability are associated with the WAI, especially in the northwest and on the borders of mountain areas. In the central area and along the Mediterranean coast there are also high probability values mainly associated with the WUI.

These two variables, as already seen above, have the highest explanatory load in the model according to Student's t values, both being interfaces significant to more than $p<0.05$, in some locations reaching more than 99%. The mapping also evidences the importance of the explanatory variables with linear deployment, such as power lines, railroads, and forest tracks.

Table 2. Successfully classified points. Top, period 1988-2007. Bottom, period 2008-2011.

1988-2007	**% Predicted**		
% Observed	**High**	**Low**	**% Marginal**
High	31.4	11.5	42.9
Low	1.5	55.5	57.1
% Marginal	33.0	67.0	100.0

2008-2011	**% Predicted**		
% Observed	**High**	**Low**	**% Marginal**
High	17.8	21.0	38.8
Low	0.1	61.1	61.2
% Marginal	17.9	82.1	100.0

3.2. Model performance

The average local R^2 obtained from the calibration sample yielded a value of 0.7, ranging between 0.19 and 0.85. As seen in Figure 7, the minimum values of R^2 were located on the Cantabrian coast, mainly in the principality of Asturias. The presence of such low values is due mainly to the absence of WAI and WUI, which have virtually no spatial representation in this region. To try to correct these values, we considered different predictive variables that could explain the occurrence in this area. Specifically, several models were adjusted to include variables such as extensive livestock and WGI.

In the case of extensive livestock, the contribution in the models was not significant, so it was eventually rejected. In the case of WGI, despite it being significant at $p<0.05$, its explanatory sense was negative, so this was considered inconsistent and the variable was also rejected. Regarding the percentage of correctly classified points, Table 2 shows the classification for the two periods examined. In the period 1988-2007, the overall percentage of success was 87% with a Kappa value of 0.73. In turn, the overall success obtained using the 2008-2011 sample was 78% with a Kappa value of 0.49. The reason for the lower success rate in the second validation sample is that the model underestimates the actual occurrence of the period, possibly because the shortest period of data collection distorts the classification of the density of high or low occurrence due to a lower number of registered fire events.

On the other hand, the GWLR model shows a little performance improvement when compared to its GLR version in terms of accuracy (Kappa), relative goodness of fit (AIC), and residuals. The GLR was adjusted and validated with the same sample as in GWLR but using two different sets of explanatory variables. A first GLR model was developed using the same variables, which resulted significant according to the GWLR model, and a second model was calibrated following a step-forward procedure to select the explanatory variables. This gave the significant variables WAI, WUI, railroads, forest tracks, and the percentage of owners of holdings aged over 55 years. Table 3 summarizes the comparison of the models.

As has been stated before, the GWLR model shows a small improvement compared to the global models in terms of accuracy and AIC. However, analysis of the residuals through the overall value of the sum and mean of residuals in mismatching locations reveals that the GWLR has lower residual values and, accordingly, a better model adjustment. In any case, GWR techniques are not design just for improve model performance; rather it is focused on exploring significant spatial varying relationships among the explanatory factors (Fotheringham *et al*., 2002).

Table 3. Comparison of GWRL and GLR models.

	GWLR	**GLR with GWLR variables**	**GLR step forward**
AIC	2426	2623	2611
Kappa value	0.726	0.715	0.714
Sum of Res	248.2	268.0	268.3
Mean of Res	0.79	0.82	0.82
Stdev of Res	0.11	0.10	0.10

3.3 Comparison with other studies

This section compares the results of the current paper with similar studies, specifically Martínez *et al*. (2013) and Chuvieco *et al*. (2010). These works were selected for comparison as they were used as background references for our study.

Martínez *et al*. (2013) calculated the probability of human-caused wildfire occurrence for the entire Spanish territory (excluding the Autonomous Region of Navarra due to a lack of data) at municipality level. The probability model was developed using GWR techniques for the period 1983-2007. Chuvieco *et al*. (2010) presented a framework for wildfire risk estimation by integrating several parameters, one of which was the probability of human-caused forest fires occurrence.

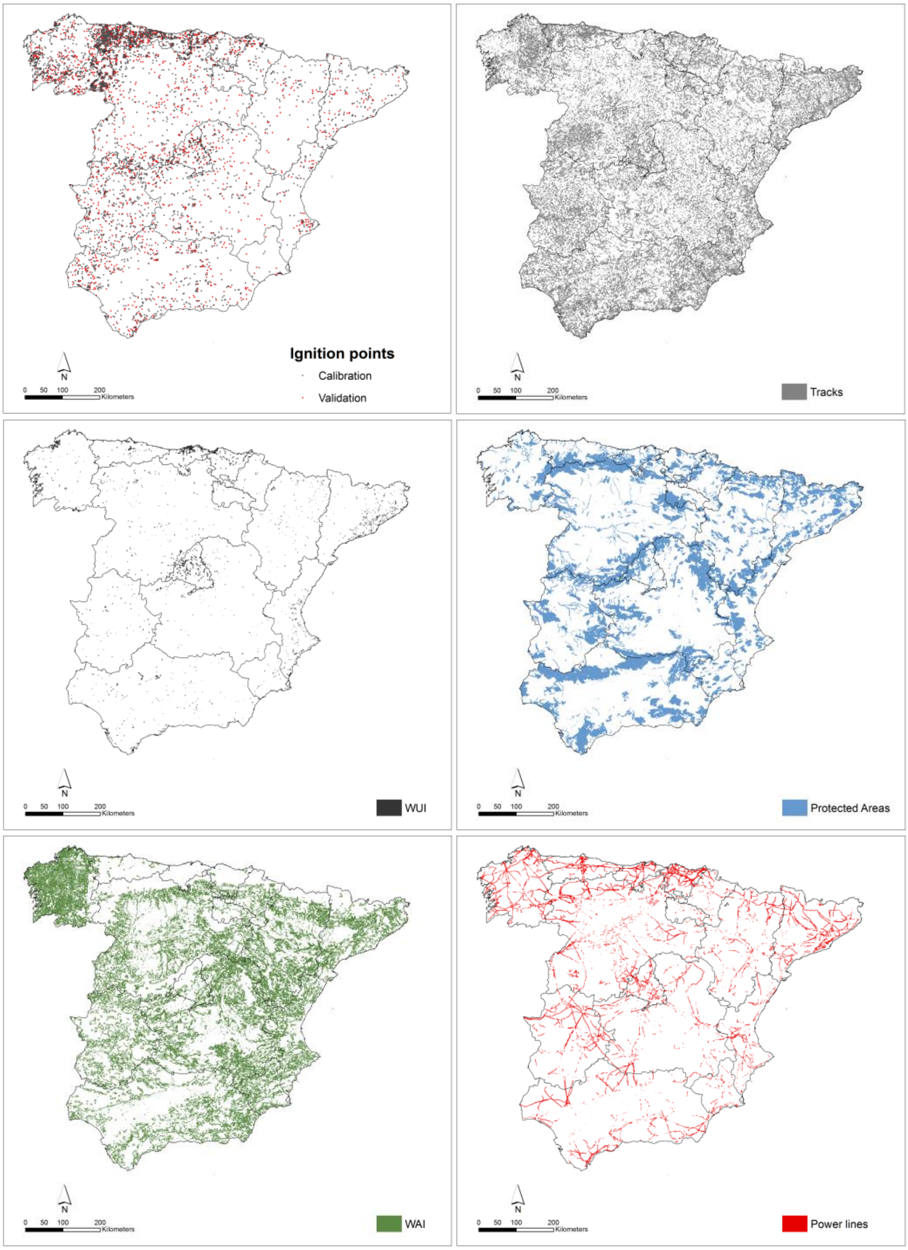

Figure 3. Variables considered in the GWLR model (cont.).

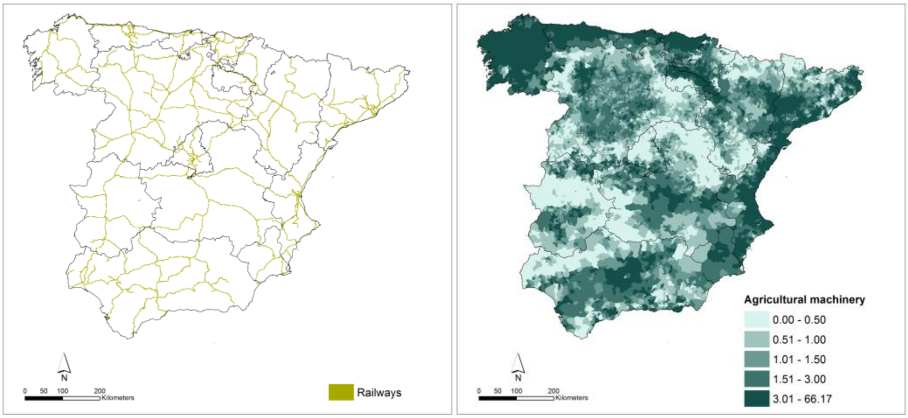

Figure 3. Variables considered in the GWLR model.

The calculation was also conducted using logistic regression, though in this case with a spatial resolution of 1x1 km and for the period 1990-2004. In contrast to Martinez *et al*. (2013) and our study, in Chuvieco *et al*. (2010) the model was restricted to four Spanish regions considered representative of wildfires in Spanish Mediterranean environments (the Community of Madrid, the Community of Valencia, the Province of Huelva, and Aragon). The comparison is summarized in Table 4.

The method followed in Chuvieco *et al*. (2010) is similar to that of the current study, except for our use of geographically weighted regression techniques. In consequence, the results are also similar in terms of explanatory variables (WUI, WAI, protected areas, power lines, and forest tracks). In contrast, however, the overall percentage of agreement of the model is considerably higher in the current study. On the other hand, despite the fact that the results in Martinez *et al*. (2013) refer to municipalities, there are some commonalities, such as the use of GWLR or the high explanatory power of WAI. Regarding the percentage of success, the overall performance in this paper is higher (87% and 78.4% for the current study and Martinez *et al*. (2013), respectively), possibly due to the way in which the regression variables have been constructed. Martinez *et al*. (2013) proposes the municipality as reference spatial unit and therefore both method and results are developed on this basis, which may lead to potential inaccuracies. We believe that our result can be considered a relative improvement, since it provides a better spatial representation of the probability of ignition and better accuracy in the prediction.

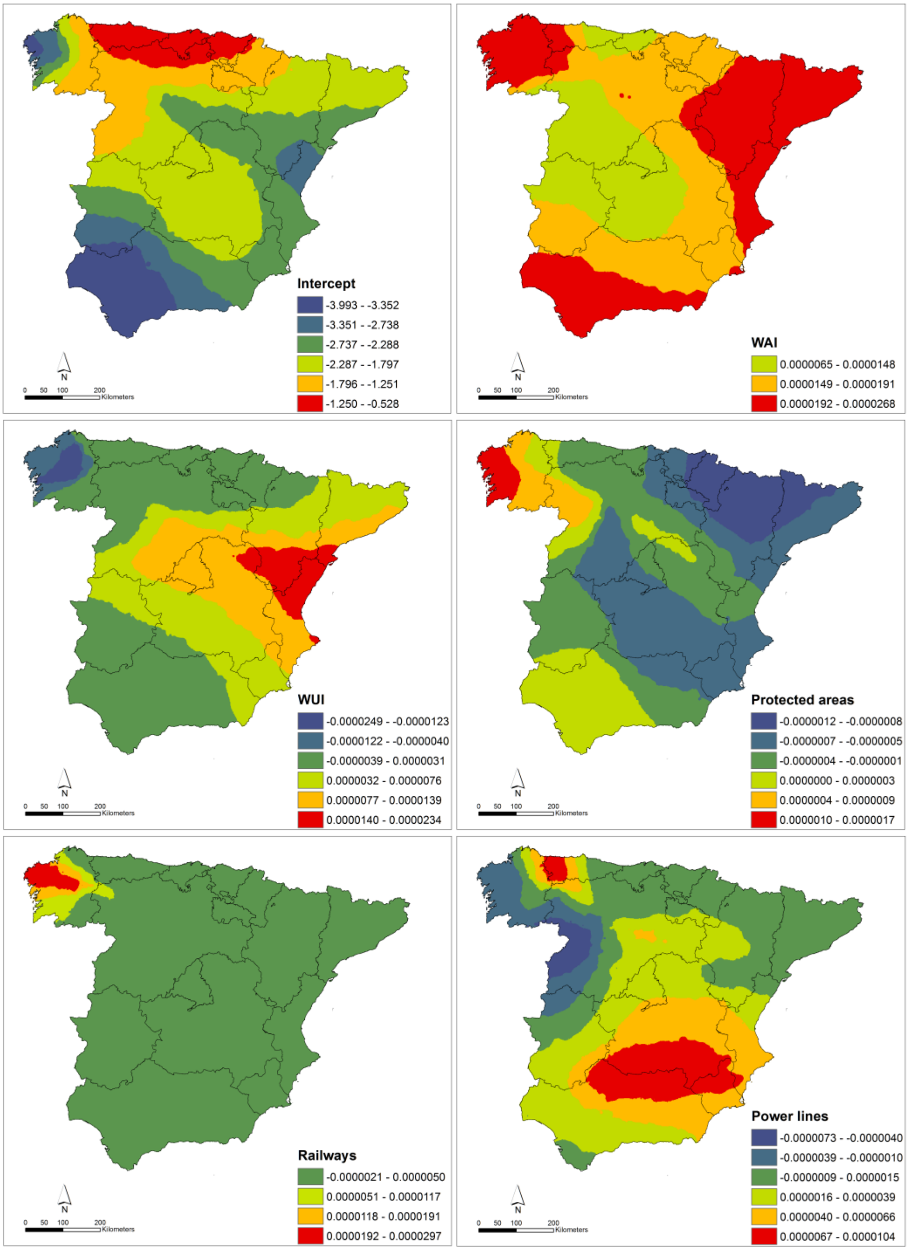

Figure 4. Regression coefficients for the explanatory variables in the GWLR model (cont.).

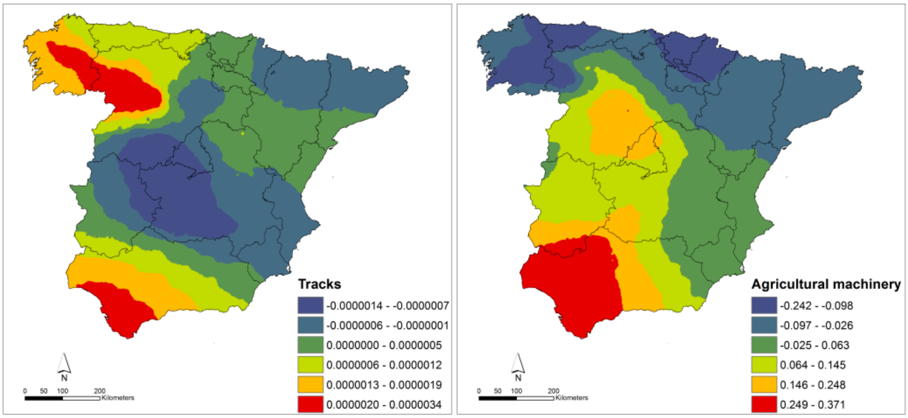

Figure 4. Regression coefficients for the explanatory variables in the GWLR model.

Table 4. Comparison with other studies. Light gray represents explanatory variables common to the current study and Chuvieco *et al*. (2010) and dark gray the current study and Martinez *et al*. (2013).

	Martinez *et al.* (2013)	Chuvieco *et al*. (2010)				Current study
		Madrid	Valencia	Huelva	Aragón	
Model accuracy	78.4%	70.6%	68.4%	84.4%	86.8%	87.0%
Period	1983-2007	1990-2004				1988-2007
WAI	X	-	-	-	X	X
WUI	-	X	-	-	-	X
Protected areas	-	X	-	-	-	X
Railroads	-	-	-	-	-	X
Tracks	-	-	-	X	-	X
DAM	-	-	-	-	-	X
Power lines	-	-	-	-	X	X
Land use change	-	-	-	X	X	-
% Forest area	X	-	-	-	-	-
Rural exodus 1950-1991	X	-	-	-	-	-
Forest area with less management	X	-	-	-	-	-
Mean annual precipitation	X	-	-	-	-	-
Mean summer temperature	X	-	-	-	-	-
Decrease in agricultural area	X	-	-	-	-	-
CORINE 243 category	X	-	-	-	-	-
Demographic potential	X	-	X	X	-	-

Table 1. Results from the colinearity analysis. Spearman's Rho rank correlation index.

	WUI	**WAI**	**WGI**	**MUP**	**PA**	**VARPOT**	**LUC**	**UR**	**PS**	**OWN55**	**DAM**	**EXTLIVS**	**PWL**	**RAIL**	**TRACKS**
WUI	1.00	0.05	0.03	-0.06	-0.04	0.12	0.01	-0.03	-0.16	0.01	0.06	0.00	0.14	0.15	0.07
WAI	0.05	1.00	-0.31	-0.29	-0.18	0.26	-0.04	-0.09	-0.09	0.13	0.06	-0.30	0.03	-0.02	0.01
WGI	0.03	-0.31	1.00	0.16	0.04	-0.20	-0.02	0.00	0.12	-0.14	0.06	0.25	0.03	0.05	0.07
MUP	-0.06	-0.29	0.16	1.00	0.14	-0.15	0.02	-0.08	0.11	-0.15	-0.04	0.09	-0.03	-0.05	-0.08
PA	-0.04	-0.18	0.04	0.14	1.00	0.02	0.02	0.07	0.06	-0.05	-0.18	-0.05	-0.05	0.00	-0.05
VARPOT	0.12	0.26	-0.20	-0.15	0.02	1.00	-0.03	-0.08	-0.40	0.02	-0.21	-0.29	0.05	0.01	-0.02
LUC	0.01	-0.04	-0.02	0.02	0.02	-0.03	1.00	-0.07	0.03	0.04	0.04	0.02	0.02	-0.01	-0.03
UR	-0.03	-0.09	0.00	-0.08	0.07	-0.08	-0.07	1.00	-0.26	0.09	-0.26	0.04	-0.05	0.02	-0.02
PS	-0.16	-0.09	0.12	0.11	0.06	-0.40	0.03	-0.26	1.00	-0.26	0.12	0.15	-0.12	-0.15	-0.06
OWN55	0.01	0.13	-0.14	-0.15	-0.05	0.02	0.04	0.09	-0.26	1.00	-0.18	-0.34	0.05	0.02	-0.03
DAM	0.06	0.06	0.06	-0.04	-0.18	-0.21	0.04	-0.26	0.12	-0.18	1.00	0.38	0.10	0.03	0.15
EXTLIVS	0.00	-0.30	0.25	0.09	-0.05	-0.29	0.02	0.04	0.15	-0.34	0.38	1.00	0.03	0.03	0.12
PWL	0.14	0.03	0.03	-0.03	-0.05	0.05	0.02	-0.05	-0.12	0.05	0.10	0.03	1.00	0.15	0.07
RAIL	0.15	-0.02	0.05	-0.05	0.00	0.01	-0.01	0.02	-0.15	0.02	0.03	0.03	0.15	1.00	0.09
TRACKS	0.07	0.01	0.07	-0.08	-0.05	-0.02	-0.03	-0.02	-0.06	-0.03	0.15	0.12	0.07	0.09	1.00

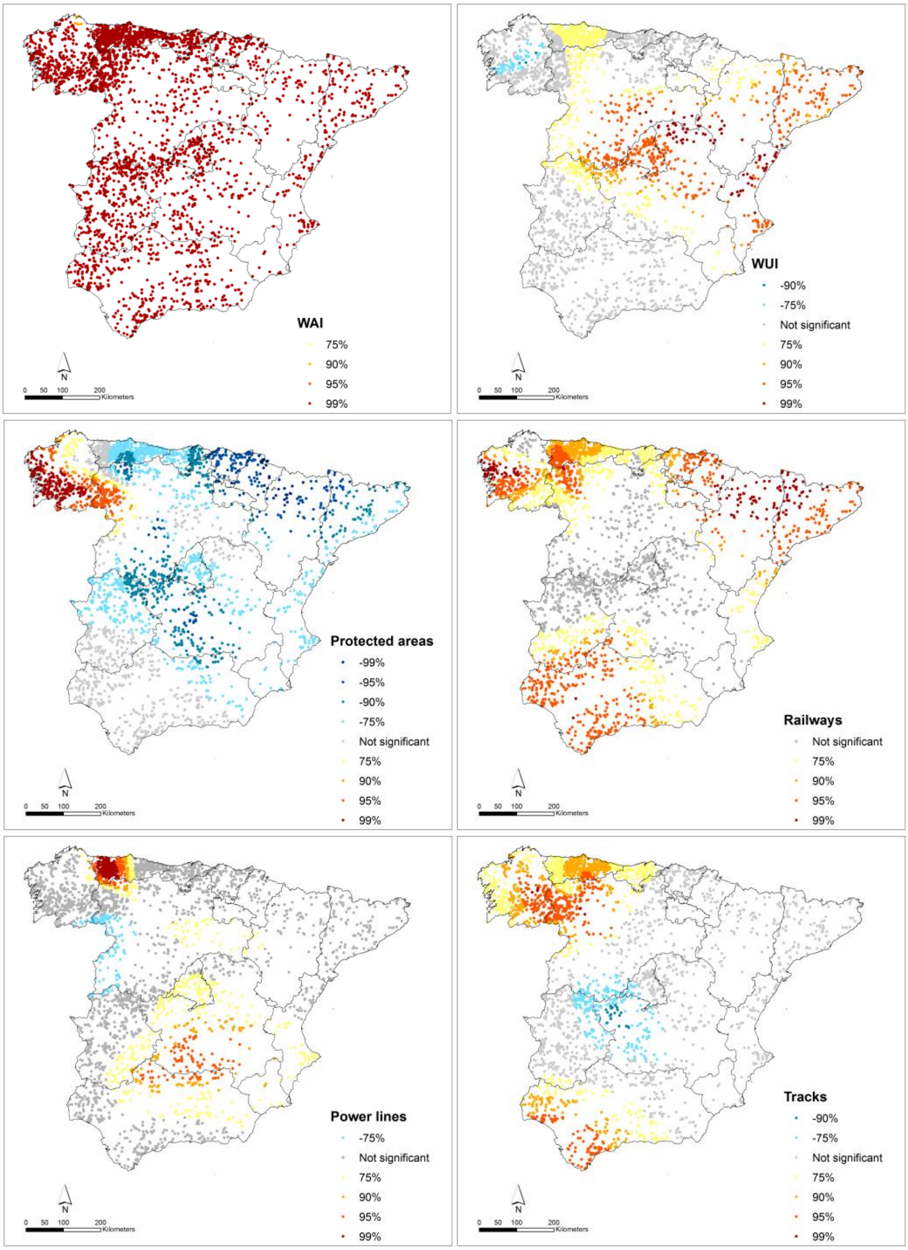

Figure 5. Significance thresholds of the explanatory variables according to Student's t in the GWLR model (cont.).

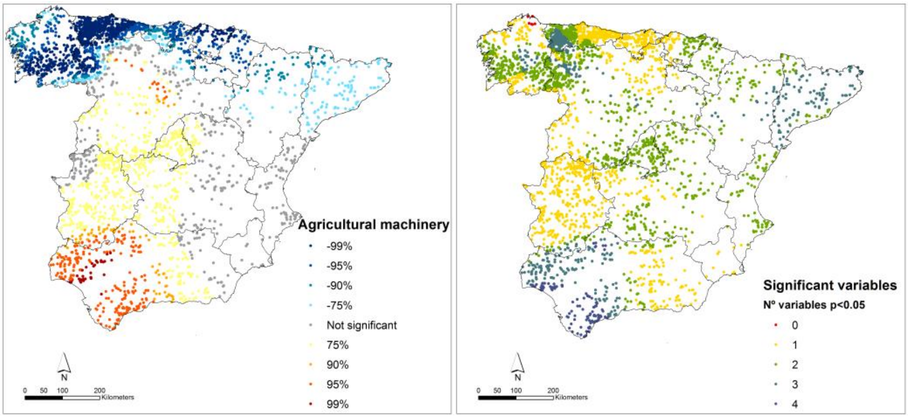

Figure 5. Significance thresholds of the explanatory variables according to Student's t in the GWLR model.

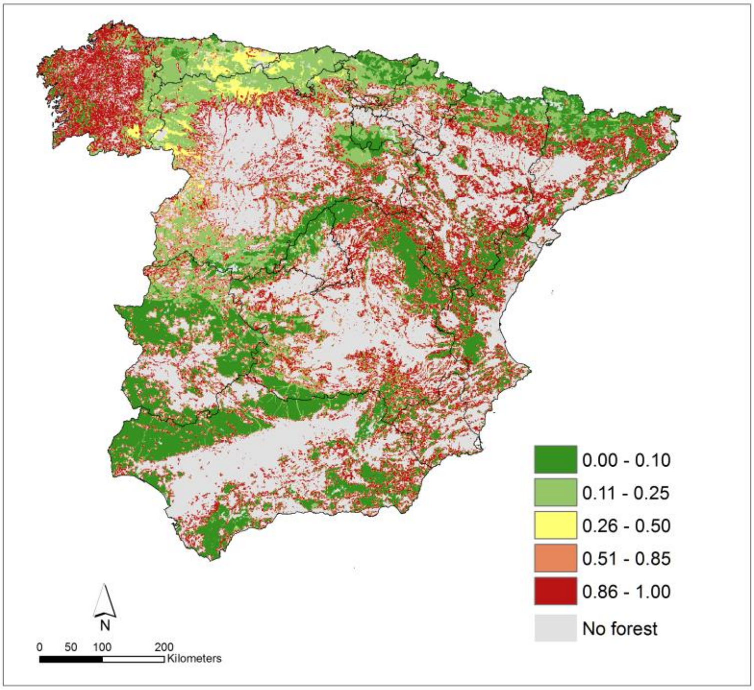

Figure 6. Probability of wildfire occurrence related to human causality.

4. Conclusions and further research

Determining which model type to use for occurrence-distribution modeling is important because the outcomes may have direct management implications. GWLR techniques have showed a high predictive potential for human-caused wildfire occurrence modeling, surpassing classical regression techniques like global logistic regression and allowing the detection of non-stationary relationships between dependent and predictive variables.

The use of GWR techniques applied to LR models has also corroborated the existence of spatial variation in the explanatory factors associated with human causality in wildfires. In addition, the validation of the results confirms that both the method used and the products obtained are consistent and sufficiently robust. However, the model still can be improved in some ways. As an example, in some areas – especially the northwest of Spain (Asturias) – there are certain mismatches, making it necessary to introduce additional independent variables for a better explanation of wildfire occurrence, specifically in relation to fires in grass and bush from February to March. On the other hand, comparison of the GWR and GLR models shows a small improvement in the accuracy, possibly due to the use of GWR techniques. This improvement is also supported by the comparison with Chuvieco *et al*. (2010).

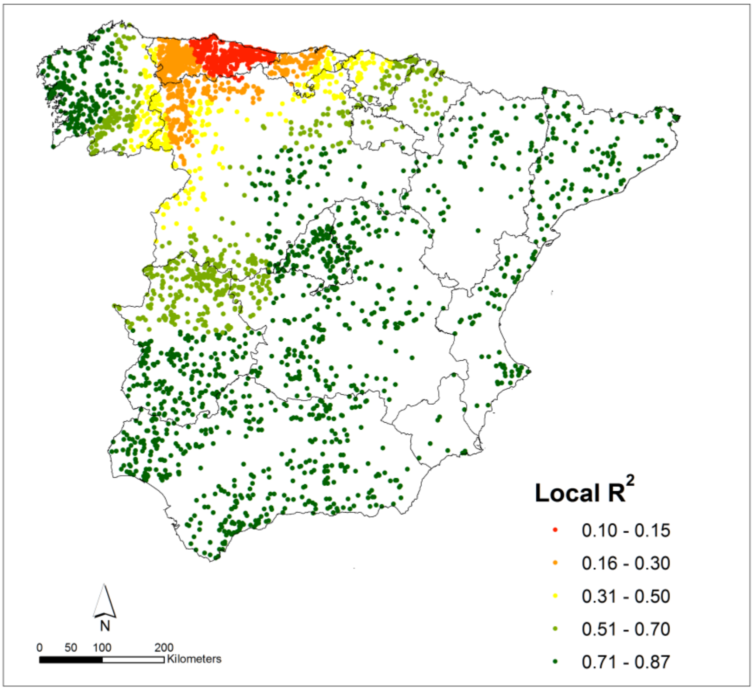

Figure 7. Local R^2 values.

Regarding the explanatory factors, as in most human-dominated landscapes where anthropogenic ignitions surpass natural ignitions, in peninsular Spain, both human accessibility (forestry tracks) and population density (WUI) are likely to be strong predictors of ignition risk(Bar Massada *et al*., 2012; Galiana-Martin *et al*., 2011). However, although these factors make an important contribution in the study, other explanatory factors more related to agricultural activities and forest management also influence wildfire occurrence. More specifically, these involve the use of fire in cleanup of harvest wastes and crop boundaries (WAI), negligence and accidents due to engines and machines working close to the forest areas (DAM), and forestry protection policies (protected areas). Nonetheless, whereas DAM, CDP, WAI, and WUI are factors related to an increased ignition probability, the presence of protected intervenes in the opposite way, i.e., by decreasing ignition likelihood, because it is directly linked with the protection and conservation of landscape. However, the WAI appears to be the most important factor related to fire ignition in Spain, its participation in the model surpassing even the WUI, and being strongly related over the whole study area. We believe this to be especially relevant, considering that the existence of areas of WUI is usually the main factor related to increased fire risk, and is traditionally considered the main human ignition factor in the literature (Galiana-Martin *et al*., 2011; Martínez *et al*., 2009; Romero-Calcerrada *et al*., 2010; Syphard *et al*., 2007; Vilar del Hoyo *et al*., 2008).

In future research, we will explore new predictors as well as new methods for spatialization (distance to the interface, density maps and so on). In addition, we will consider the temporal dimension in fire risk assessment with the aim of developing dynamic models.

Acknowledgements

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An insight into machine-learning algorithms to model human-caused wildfire occurrence

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Abstract

This paper provides insight into the use of Machine Learning (ML) models for the assessment of human-caused wildfire occurrence. It proposes the use of ML within the context of fire risk prediction, and more specifically, in the evaluation of human-induced wildfires in Spain. In this context, three ML algorithms—Random Forest (RF), Boosting Regression Trees (BRT), and Support Vector Machines (SVM)—are implemented and compared with traditional methods like Logistic Regression (LR). Results suggest that the use of any of these ML algorithms leads to an improvement in the accuracy—in terms of the AUC (area under the curve)—of the model when compared to LR outputs. According to the AUC values, RF and BRT seem to be the most adequate methods, reaching AUC values of 0.746 and 0.730 respectively. On the other hand, despite the fact that the SVM yields an AUC value higher than that from LR, the authors consider it inadequate for classifying wildfire occurrences because its calibration is extremely time-consuming.

Keywords: Machine learning; model; wildfire; Random Forest; Boosted Regression Tree; Support Vector Machine.

1. Introduction

Concern about wildfires and their impacts is an increasing phenomenon. In Mediterranean Europe, increasing trends in the number of fires have been detected in some countries such as Portugal and Spain (San-Miguel-Ayanz *et al*., 2012). This increase in wildfire frequency, with its associated risks to the environment and society (Moreno *et al*., 2011), calls for better understanding of the processes that control wildfire activity(Bar Massada *et al*., 2012). Therefore, a better comprehension of the driving forces of fire ignition and of predicting where fires are likely to start are core elements in designing strategies to mitigate wildfire initiation and to identify areas at risk (Finney, 2005). Consequently, efforts to achieve a better understanding of wildfires have been increasing in recent years, and several methods for wildfire risk assessment have been developed using different methodological schemes, variables, and scales (Martínez-Vega *et al*., 2012). Without being exhaustive, some of the more recent efforts have included those by Amatulli *et al*. (2006), Chuvieco *et al*. (2012, 2010), Cooke *et al*. (2007), Loboda (2009), Martínez *et al*. (2009,2011), Martinez and Koutsias (2013), Padilla and Vega-Garcia (2011), and Romero-Calcerrada *et al*. (2010). Within the same context, similar efforts have been invested in modeling fire occurrence (see Plucinsky (2011) for an exhaustive review), one of the main input parameters when modeling wildfire risk (Chuvieco *et al*., 2012).

On the other hand, human beings have a great impact on fire regimes because they alter ignition frequency and fuel fragmentation and suppress fires (Guyette *et al*., 2002). The dynamics of fire regimes in southern Europe are related mainly to human factors, which are the cause of more than 95% of fires in this region (San-Miguel Ayanz and Camia, 2009). The analysis of human factors in forest fires is widely recognized as of critical importance for fire danger estimation (Kalabokidis *et al*., 2002; Martínez *et al*., 2004b), but the literature on this topic is scarce and mainly site-specific (Krawchuk *et al*., 2009; Le Page *et al*., 2010; Martínez *et al*., 2009). However, in recent years, the role of human factors in fire behavior modeling has been increasing, and several models now include an anthropogenic component in their assessments (Chuvieco *et al*., 2012, 2010; Loepfe *et al*., 2011). Machine learning (ML) models have shown their predictive accuracy in data mining and other disciplines (Casalegno *et al*., 2011; Cutler *et al*., 2007; Diaz-Uriarte and Alvarez de Andres, 2006; Drake *et al*., 2006; Li *et al*., 2011; Marmion *et al*., 2009; Pino-Mejías *et al*., 2010; Shan *et al*., 2006). Previous studies have also proposed ML algorithms to model the spatial distribution of wildfire occurrence or ignition. These algorithms include Regression Trees (RT; Amatulli *et al*., 2006), Artificial Neural Networks (Vasconcelos *et al*., 2001; Vega-Garcia *et al*., 1996), and more recently, Random Forest (RF; Bar Massada *et al*., 2012). However, these methods have not been widely used to model human-caused wildfire occurrence at a regional scale or for large occurrence datasets; this is therefore the main goal of this work. This topic will be addressed in greater depth by exploring other stochastic and deterministic ML algorithms and their application to the Spanish territory. Specifically, the performance of Random Forest (RF), Boosted Regression Trees (BRT), and Support Vector Machines (SVM) has been explored, and their outcomes have been compared with those from binary logistic regression (LR), a commonly used technique for probabilistic explanation of human-caused occurrences (Chuvieco *et al*., 2010; Martínez *et al*., 2009, 2004a; Vasconcelos *et al*., 2001; Vega-Garcia *et al*., 1995).

The main drawback of modeling with only one RT is that this approach is not entirely robust because each division can involve a set of variables with similar discriminatory power. Therefore, small changes in the data can generate very different models. To avoid such problems, researchers have recently shown interest in ensemble learning methods. These methods generate many classifiers and enable grouping of the results in a final classification. Two examples of well-known ensemble methods are boosting and bagging (Breiman, 2001; Hastie *et al.*, 2009; Hernández Ramírez and Ferri, 2004; Sierra, 2006). Boosting is a method for improving model accuracy, based on the idea that it is easier to find and average many rough empirical rules than to find a single, highly accurate prediction rule (Schapire, 2003). Related techniques—including bagging, stacking and model averaging—also build, then merge results from multiple models, but boosting is unique because it is sequential (Elith *et al.*, 2008). On the other hand, bagging is a technique designed to create training data sets resampled randomly with replacement of original data, i.e., without removing the selected data set before selecting the next subset. Thus, data may be used more than once to train individual classifiers. This property makes bagging methods less sensitive to slight variations in the input data (training changes, outliers, noise ...) and at the same time increases the accuracy of classifications (Breiman, 2001).

RF is an ensemble classifier using decision trees as base classifiers. The RF algorithm was proposed by Breiman (2001) and adds an element of randomness to bagging, increasing the diversity of decision trees by growing them from different subsets. Besides generating each decision tree using a subset of different training elements in each iteration, RF changes the way that the decision tree is generated by the classification. In the creation of decision trees in the CART algorithm, each node is split using the best threshold for all variables introduced, while in RF, the nodes are divided using the best variables from a random sample. This modification, although somewhat counterintuitive, has proven to be a strategy that gives very good results compared to other classifiers with completely different approaches or to other decision-tree algorithms (Liaw and Wiener, 2002). For the final classification of each element, each generated random tree provides a simple vote, and the algorithm finally assigns the class that received the most votes (Liaw and Wiener, 2002).

The BRT model uses two algorithms: regression trees for classification and regression, and boosting for combining a collection of models (Elith *et al.*, 2008). The BRT approach differs fundamentally from traditional regression methods that produce a single best model. Instead, BRT uses boosting to combine large numbers of relatively simple tree models to optimize predictive performance (Elith *et al.*, 2006; Leathwick *et al.*, 2008, 2006). The boosting approach used in BRT places its origins within ML (Schapire, 2003), but subsequent developments in the statistical community have reinterpreted it as an advanced form of regression (Friedman *et al.*, 2000).

On the other hand, the SVM algorithm is based on making highly reliable predictions, even at the risk of making some mistakes. To this end, SVM tries to find the optimal hyperplane of separation between the classes, i.e., the plane in which the separability between classes is a maximum. The examples located on this hyperplane are called support vectors. These examples are the most difficult to classify since they have lower separability. In the simplest case, two classes in a two-dimensional space in which the data are linearly separable, the optimal hyperplane would be defined by a straight line. For a more detailed description of SVM operation, see Vapnik (1998, 1995).

In this work, several models using these three ML algorithms were investigated in the Spanish territory. Spain is one of the countries more affected by forest fires in Europe (Rodrigues *et al*., 2013; San-Miguel-Ayanz *et al*., 2012), thus it could be considered a key area for testing and improving wildfire risk models at European scale. The results from the ML models were compared to LR outcomes, also calculated in this paper, to test their performance. All models were fitted using the same explanatory and dependent variables. The explanatory variables (later introduced and described) were selected on the basis of the authors' previous experience with models at regional and national scales (Amatulli *et al*., 2007; Chuvieco *et al*., 2012, 2010; Martínez *et al*., 2004b; Vilar del Hoyo *et al*., 2008), while the dependent binary variable (high/low fire occurrence) was constructed from wildfire observations from 1988 to 2007 in Spain. Results suggest that ML models improve LR both in terms of prediction accuracy and of the spatial pattern of the probability of occurrence. However, SVM requires a more in-depth exploration and optimization to be properly calibrated for wildfire occurrence prediction.

2. Materials and methods

2.1 Study area

The study area covered the whole of peninsular Spain, excluding the Balearic and Canary Islands, as well as the autonomous cities of Ceuta and Melilla, because some parameters needed to develop the methodology were not available in those areas. Therefore, the total area of the study region was approximately 498,000 km^2. Moreover, the study region was restricted to forested areas. Consequently, urban areas, agricultural areas, and inland water zones were excluded from the assessment, and no data for them are detailed or displayed in the maps. Spain is a territory of wide contrasts which presents a great variety of climatic, topographic, environmental, and other biophysical conditions. These dissimilar conditions also appear when talking about socioeconomic conditions in terms of population systems and population structure, productive sectors, or geographic structure. Therefore, the complexity of the socioeconomic conditions play a determining role and are especially important when modeling human factors because this complexity is transferred to the relationships between socioeconomic variables and to natural phenomenon like wildfires, making their assessment more difficult.

2.2 Dependent variable

The dependent variable—high/low wildfire occurrence—was built from the Spanish EGIF (General Statistics of Wildfires) database from 1988 to 2007. The EGIF database is one of the oldest "complete" wildfire databases in Europe, beginning in 1968 (Vélez, 2001). It has been compiled by the Ministry of Environment, Rural, and Marine Affairs (MARM) using forest fire reports from the various autonomous regions (Moreno *et al.*, 2011). Among other useful information relating fire events, these reports include data regarding the starting location point of each fire. This position is recorded on the basis of a reference 10x10 km ICONA grid (used by the firefighting services for approximate location of fire events) and the municipality origin of the ignition. The spatial distribution of fire occurrence (308,893 fires in the period from 1988 to 2007, as shown in Figure 1) was developed through a combination of the 10x10 km grid, a digital map of Spanish municipalities and the boundaries of the forest area. More specifically the ignition location procedure is based in the method developed by de la Riva *et al.* (2004). This method is widely recognized and has been used in many wildfire assessment research works in the Spanish territory such as Amatulli *et al.* (2007), Chuvieco *et al.* (2012, 2010) and most recently in Rodrigues *et al.* (2014). The method proposes a multi-step procedure which successively refines and decreases the potential location area of the ignition points by ruling out areas where the fire could not have occurred. Firstly it starts in the 10x10 grid with a potential location area of 100 km^2. Then this area is decreased by intersecting with the boundaries of the municipality origin of the fire. Finally, the location area is restricted to the forest perimeter (MARM, 1997) – since the ignition location of every wildfire is expected to be in the forest area – to determine the final potential location area. This process leads to a significantly smaller area where the ignition points are then randomly distributed. This allowed us to calculate fire density maps with a spatial resolution of 1x1 km by overlapping the final ignition points cloud and a 1x1km UTM grid (which perfectly fits the 10x10 grid). Figure 2 illustrates this procedure. Recent studies have commented that predictions from fire simulations based on random ignitions may produce unrealistic results because the spatial distribution of ignition locations, whether human-caused or natural, is non-random (Bar Massada *et al.*, 2011).

However, the lack of explicit location data for wildfire events, especially in the first years of the EGIF dataset, made it impossible to generate a realistic set of locations. On the other hand, in many cases where coordinates have been assigned, the final location seems to be unreliable because it corresponds with unexpected sites such as the corner of the UTM grid or outside the forest area, which are more likely to be false.

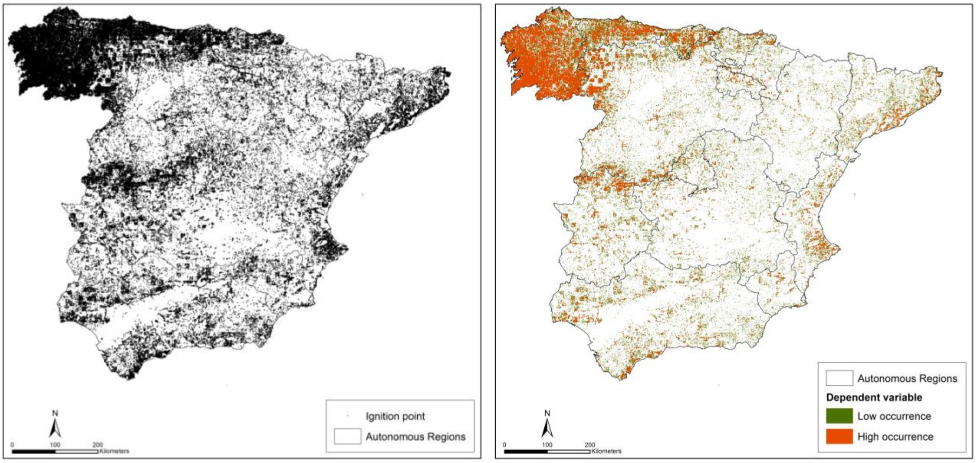

Figure 1. Spatial distribution of ignition points (left) and the dependent variable (right).

The final dependent variable was created on a conceptual framework which assumed that there were no true cases of fire absence. In ignition data, most or all of the fire occurrences are accounted for, which may make it seem as if all other locations in the landscape have no fires. In this context, most previous attempts at fire occurrence modeling had used background subsets of "no occurrence" during the analyzed time span, considering them to be true cases of fire absence (e.g., Chuvieco *et al*., 2010; Padilla and Vega-García, 2011). However, the fact that these areas did not experience an ignition event during the temporal span of the data set does not mean that they could not feasibly support an ignition event in the future, or that they never ignited in the past (Bar Massada *et al*., 2012). In line with this reasoning, the dependent variable was developed by classifying the occurrence values into two categories: high occurrence (presence; 27956 points) in locations with two or more fires, and low occurrence (pseudo-absence or background; 28188 points) in locations with only one fire (Figure 1). The authors thought that the consideration of low-occurrence locations as pseudo-absences was more realistic than the creation of random background subsets. The fact that these areas have experienced only one fire event in a long time span (20 years), means that their characteristics are strongly related with low fire frequencies.

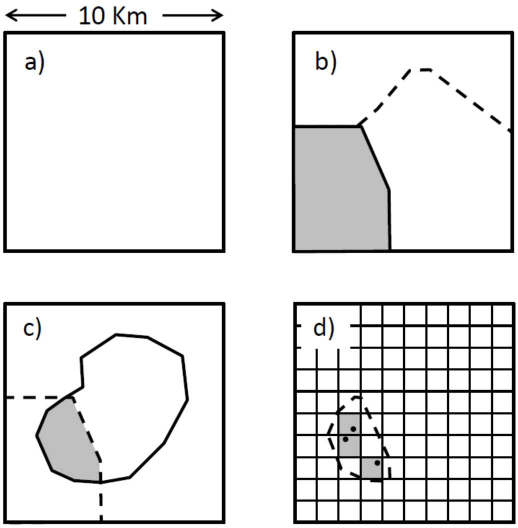

Figure 2. Procedure for ignition points location. Potential location area is grey-colored. a) 10x10 km ICONA grid; b) municipality intersection; c) forest area intersection; d) random point location and intersection with 1x1 km grid.

2.3. Explanatory variables

The explanatory variables were selected and spatialized on the basis of the authors' experience with models at regional and national scales (Amatulli *et al*., 2007; Chuvieco *et al*., 2012, 2010; Martínez *et al*., 2004a; Vilar del Hoyo *et al*., 2008). According to this, the explanatory variables were classified in relation to the typology of the affecting factor (Leone *et al*., 2009; Martínez *et al*., 2004b), as follows:

1. Factors related to socio-economic transformations.
   1.1. Abandonment of traditional activities in wildland and rural areas, especially in privately owned forests with no prospect of economic profit. Little or no interest in forest conservation.
   - ***Forestry area in public utilities.*** Delimitation of the area occupied by forestry areas included in the public utility catalog.

   1.2. Human presence, population increase, and urban growth. More pressure on wildlands.
   - ***Wildland-Urban Interface (WUI).*** Area occupied by the 200-meter buffer from the line of contact to the forest area. Constructed from the Spanish Forestry Map 1:200000 (MFE200).
   - ***Changes in demographic potential 1991-2006*** (Calvo and Pueyo, 2008)**.** Variation rate between the demographic potential in 1991 and in 2006. Demographic potential is an aggregate index

related to the ultimate future potential of the population. It reflects the demographic power of the nation and its ability to provide future population growth (Ediev, 2001).

2. Factors related to traditional economic activities in rural areas.

   2.1. Agriculture. Fire use to eliminate harvesting wastes and to clean cropland borders.

   - ***Wildland-Agricultural Interface (WAI).*** Area occupied by the 200-meter buffer from the line of contact to the forest area. Constructed from the Spanish Forestry Map 1:200000 (MFE200).

3. Factors which could cause fire mainly by accident or negligence.

   3.1. Electric lines. Possible cause of ignition by accident.

   - ***Power lines.*** Area occupied by the 50-meter buffer around the high-, medium-, and low-voltage transport network. Obtained from BCN200.

   3.2. Engines and machines working in or close to forest areas. Possible cause of ignition by accident or negligence.

   - ***Density of agricultural machinery.*** Obtained at the municipal level from the Agricultural Census 1999 of the Spanish Statistics Institute (INE).

   3.3. Presence of roads, railways, and tracks and their accessibility. More human pressure on wildland.

   - ***Railways.*** Area occupied by the 200-meter buffer around the railroad network (excluding the high-speed network). Obtained from a digital cartographic database (BCN200).

4. Factors which could hamper fires.

   4.1. Protected areas. Increasing concern about forest protection.

   - ***Protected areas.*** Delimitation of the area occupied by natural protected areas and the Natura 2000 network.

All the predictive variables, as well as the dependent variable, were distributed in space at a resolution of 1x1 km. To ensure consistency of results, a collinearity analysis of the explanatory variables was carried out. No collinear variables were found.

2.4 Model calibration and software

The models were fitted using the R statistical software (packages randomForest, gbm, and kernlab). R is an open-source statistical programming language developed as a large collaborative project by statisticians from different countries and disciplines (R Development Core Team, 2008). The total sample obtained from the spatial distribution of the fire reports compiled in the EGIF database (93573 locations with fire) was separated into a training sample (60% of the population) and a testing sample (40% of the population). Consequently, the calibration sample was made up of 56144 fire records and the validation sample of 37429. The explanatory variables were considered or not considered, depending on the model, according to the value of the area under the receiver operating characteristic curve (AUC) of the trained model (see Section 2.5); variables were introduced when they improved the AUC value and dropped when the AUC remained at the same or a lesser value.

2.4.1 RF

RF can be parameterized according to the number of trees averaged in the ensemble forest (*ntrees*), the number of predictor variables randomly selected at each iteration (*mtry*), and the minimum number of observations at end nodes (*nodesize*), which can decrease the length of nodes in tree branches and simplify trees. All combinations of five *ntrees* levels (1000, 2000, 3000, 4000, and 5000) and three mtry levels (from 1 to 3) were tested. The *nodesize* parameter was left at its default value. The values of the parameters in the final model were *mtry*=2 and *ntrees*=3000. Models with higher values of these parameters did not improve accuracy.

2.4.2 BRT

A BRT model can be tuned using several parameters such as the number of nodes in a tree (*tree complexity*), the contribution to the model of each tree (l*earning rate*), the proportion of data to be selected at each step (*bag fraction*), and the average number of trees in the ensemble forest (*ntrees*). According to Elith *et al*. (2008), a decreasing (slowing) learning rate increases the value of *ntrees* required, and in general, a smaller value of learning rate (and a larger value of *ntrees*) is preferable, conditional on the number of observations and the time available for computation. All combinations of five *ntrees* levels (1000, 2000, 3000, 4000, and 5000) and five values of *learning rate* (0.05, 0.01, 0.005, and 0.001) were tested, resulting in optimum values of 3000 for *ntrees* and a *learning rate* of 0.005. The values corresponding to *tree complexity* and *bag fraction* were set at 5 and 0.5 respectively for each combination of ntrees and learning rate.

2.4.3 SVM

An SVM model requires a large number of parameters to be optimized: *kernel functions* (linear, polynomial, sigma, or radial basis), *cost*, the *gamma* of the *kernel function* (except the linear kernel), the bias of the *kernel function* (applicable only to the polynomial sigmoid kernel), and finally the *polynomial degree* (applicable only to the polynomial kernel). For this reason, the optimization of an SVM model is more complicated than optimization of RF or BRT. The SVM model was calibrated using the R package kernlab. The parametrization of the model was done as follows: *type = C-bsvc, kernel = rbfdot with kpar = sigma(0.1)*. The *cost* was set to a range of values from 1 to 10 and was finally left at 1. The authors were aware that further testing of the parameters involved in SVM calibration was needed, but the lack of available computing power and the resulting long run times did not permit proper exploration of these issues.

2.4.4 LR

LR models are statistical models which provide insights into the relationship between a qualitative dependent variable, dichotomous in the present case, and one or more independent explanatory variables, whether qualitative or quantitative. The mathematical expression of LR models is:

$$y_i = \frac{e^{(\beta_0+\beta_1 x_{1i}+...+\beta_k x_{ki})}}{1+e^{(\beta_0+\beta_1 x_{1i}+...+\beta_k x_{ki})}}.$$

In this work, the LR model was developed using a forward stepwise procedure in which the explanatory variables were introduced into the model one by one according to the resulting improvement in the model, as measured by the Akaike Information Criterion (AIC).

2.5 Model evaluation and comparison

To calculate and compare the classification accuracy of the four models, the area under the receiver operating characteristic (ROC) curve (AUC, Hanley and McNeil, 1982) was calculated. The ROC curve is a graphical representation of the false-positive error (1 – specificity, where specificity is the proportion of incorrect predictions) versus the true positive rate (also referred as sensitivity or the proportion of correct predictions) for a binary classifier system and for different values of the discrimination threshold (Zhou *et al.*, 2011). The AUC is a threshold-independent metric because it evaluates the performance of a model at all possible threshold values (Franklin, 2010). AUC values ranged from 0.5 to 1, where 0.5 is analogous to a completely random prediction and 1 implies perfect prediction. AUC values between 0.5 and 0.7 denote poor performance, values between 0.7 and 0.9 denote moderately good performance, and values larger than 0.9 denote excellent model performance (McCune *et al*., 2002).

2.6 Evaluating variable importance

The evaluation of variable importance in the models was carried out using two different approaches. The first involves use of model-specific procedures, i.e., the increase in node purity for RF, the relative influence of the variables for BRT, and Z values for LR. The increase in node purity is measured by the gini criterion from all the splits in the forest based on a particular variable (Breiman, 2001). Relative influence measures the number of times that a variable is selected for splitting, weighted by the squared improvement to the model as a result of each split, and averaged over all trees (Friedman and Meulman, 2003). The relative influence (or contribution) of each variable is scaled so that the sum is 100. The second method for variable importance measurement is based on an AUC procedure as a jackknife estimator of variable importance, as described by Bar Massada *et al*. (2012). This procedure is based on the fact that a binary classification system can be used to calculate receiver operating characteristic curves (ROC) and to determine the precision of a diagnostic test (Ordóñez *et al*., 2012) . Therefore, the method was based on measuring the change in AUC using the test data, a method which yields directly comparable results across the three ML models and the LR. The approach consists on removing predictor variables from the full model one at a time, training the model, and calculating the AUC using the test data. The difference between the full- and partial-model (without the variable) AUC indicates the contribution of each variable to the model. Therefore, it represents the information provided by a given variable that is not present in other variables. In addition, the AUC of the model was quantified using one variable at a time, the AUC values of single-variable models were compared, and the variables were ranked accordingly. This procedure enabled both a comparison of the accuracy of the models and a significance analysis of the explanatory variables within each model and compared to the other algorithms. Because there is no variable importance method implemented for SVM, this approach will be evaluated only using the AUC.

3. Results

3.1 Model performance

RF and BRT achieved the highest accuracy, reaching AUC values of 0.746 and 0.730 respectively. The SVM model yielded an AUC value of

0.709. The worst model accuracy was associated with the LR model, with a value of 0.686. According to the accuracy threshold proposed in McCune and Grace (2002), the ML models achieved moderate performance, while the LR had rather poor performance. Note also that RF, despite being the model with the fewest predictive variables (as reported in Table 1), reached the highest accuracy of classification (Figure 3). Table 1 shows a brief summary of model accuracy and the explanatory variables considered in each model.

3.2 Variable importance

According both to model-specific procedures and to AUC jackknife estimation, negligence and accidents due to engines and machines working in or close to forest areas, the use of fire to clean up harvest wastes and crop boundaries, the increase in human presence and pressure near wildlands, and increasing concern for forest protection are the main factors related to human-induced wildfire occurrence in Spain (Figure 3). The four explanatory variables linked to each typology of causes, i.e., density of agricultural machinery (DAM), changes in demographic potential (CDP), wildland-agricultural interface (WAI), and protected areas (PA), make a significant contribution to all models (Table 1) and therefore are included in all of them. DAM and CDP are the main variables in each variable importance method, although WAI reduces its contribution while that of PA increases in the AUC procedure.

Table 1. Model accuracy and explanatory variables. +: Variable in the model, -: variable not considered in the model. Dark grey shading indicates the predictor variables that are considered in all models.

	RF	**BRT**	**SVM**	**LR**
AUC	0.746	0.730	0.709	0.686
Wildland-Agricultural interface	+	+	+	+
Wildland-Urban interface	-	+	+	+
Protected areas	+	+	+	+
Railroads	-	-	-	+
Density of machinery	+	+	+	+
Power lines	-	-	-	+
Changes in demographic potential	+	+	+	+
Forestry area in public utilitiy	+	+	+	-

When considering each variable individually (univariate models), DAM and CDP are the two predictive variables with the highest explanatory power, with AUC values ranging from 0.669 to 0.687 and 0.630 to 0.659 respectively. This predictive power is supported by examining the models without these variables, where the losses in AUC are also the greatest. In the background, with modest AUC values, appear the rest of the variables, ordered from more to less contribution as follows: PA, WAI, FAPU, Wildland-Urban interface, power lines, and railroads (Table 2).

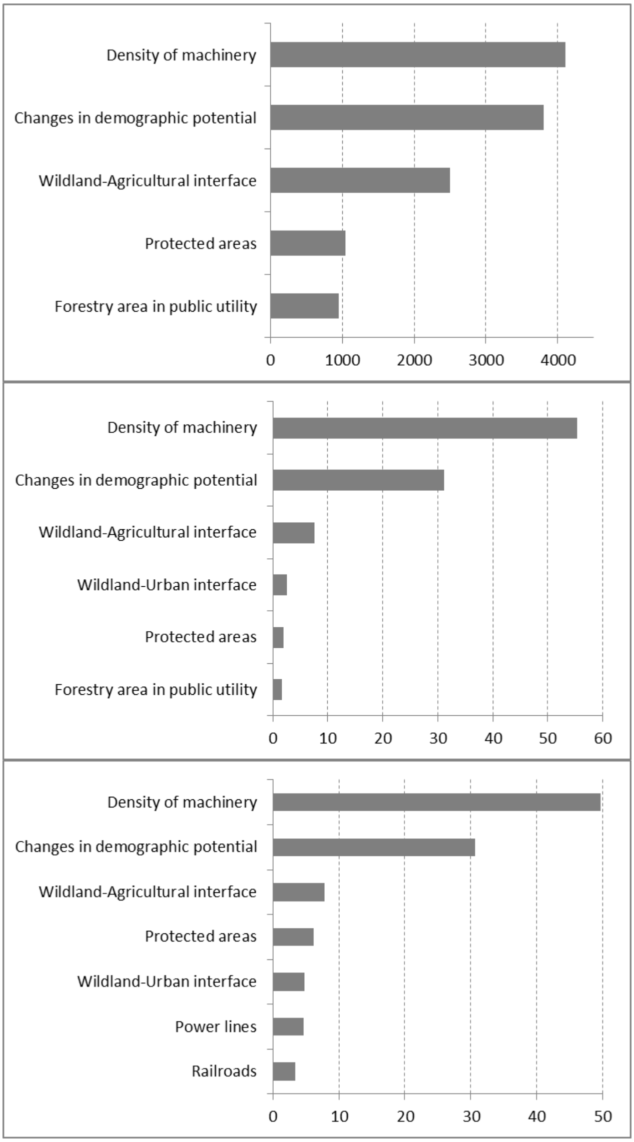

Figure 3. Increment in node purity (RF; top), relative importance (BRT; middle) and absolute Z value (LR; bottom).

3.3 Spatial distribution of occurrence probability

The mapping of the spatial pattern of predicted wildfire occurrence is significantly different from one model to another (Figure 5). A visual analysis reveals that RF has the highest spatial variability in predicted values. Despite having the same independent variables (Table 2), BRT and SVM present a very different spatial pattern. In the case of SVM, the pattern seems to be dichotomized, with probability values concentrated in two ranges close to the maximum and minimum values. On the other hand, the spatial distribution is more heterogeneous in BRT and closer to the RF distribution. Finally, the LR map shows a spatial distribution similar to BRT, but the fact that it contains almost no low probability values (in the range from 0 to 0.2) has hindered both its accuracy and its predictive power.

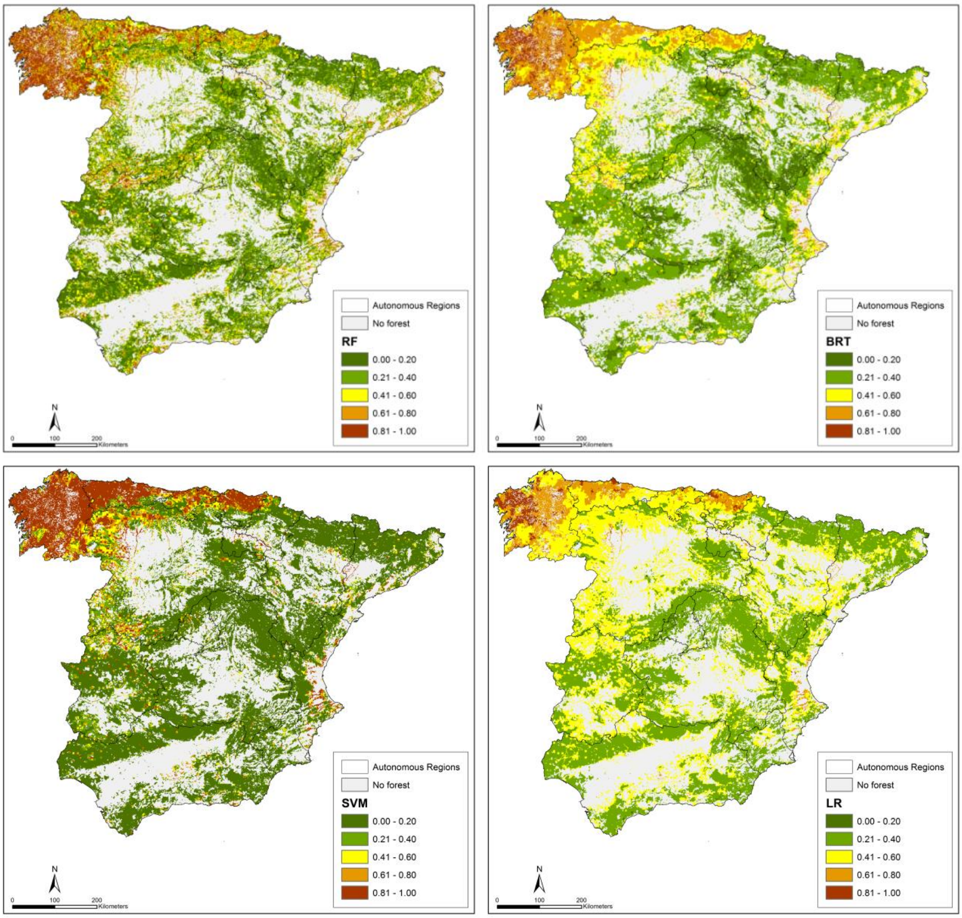

Figure 5. Spatial pattern of the probability of wildfire occurrence for each model. Top left is RF, top right BRT, bottom left SVM, and bottom right LR.

4. Discussion

Determining which model type to use for occurrence-distribution modeling is important because the outcomes may have direct management implications. Previous findings from species-distribution modeling (SDM; Franklin, 2010) for wildlife have suggested that ML algorithms may be more suitable than statistical models (Elith *et al.*, 2006).

Table 2. Summary of results from the jackknife AUC estimator.

	RF	BRT	SVM	LR	AUC	Times in model
Wildland-Agricultural interface	0.68	0.67	0.65	0.67	0.67	4
Wildland-Urban interface	0.65	0.64	0.63	0.63	0.64	4
Protected areas	0.53	0.53	0.54	0.55	0.54	4
Railroads	0.51	0.53	0.54	0.53	0.53	4
Density of machinery	0.50	0.51	0.52	-	0.51	3
Power lines	-	0.51	0.50	0.51	0.51	3
Changes in demographic potential	-	-	-	0.51	0.51	2
Forestry area in public utility	-	-	-	0.51	0.51	2

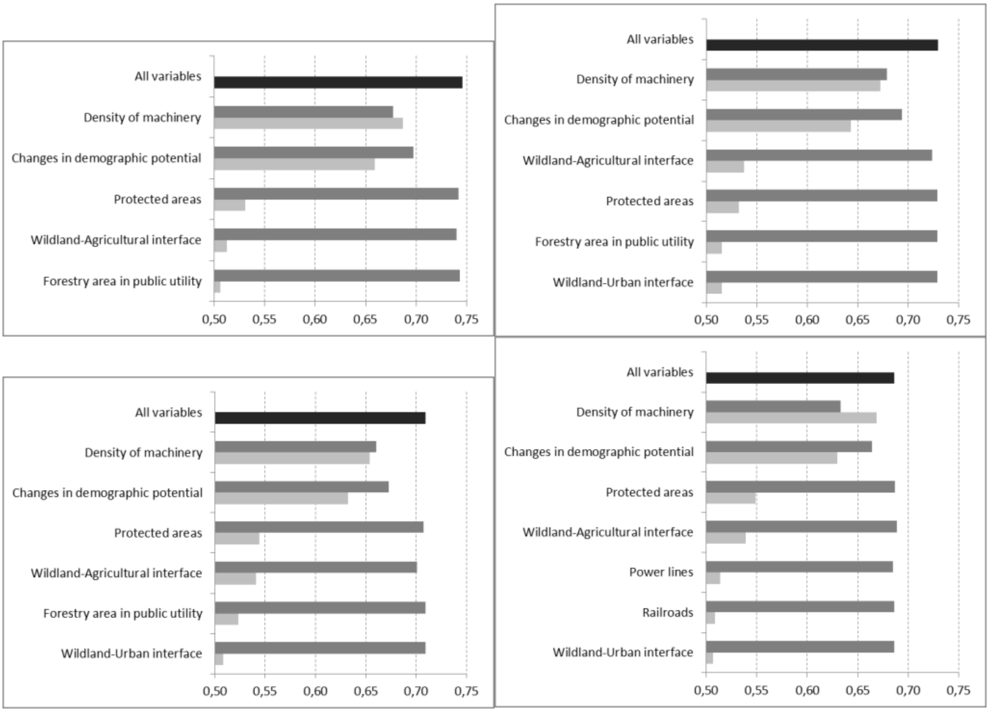

Figure 4. AUC values. In black, the final model; in dark grey, the model without the corresponding variable; and in light grey, the AUC value for a model with only the corresponding variable. Top left is RF, top right BRT, bottom left SVM, and bottom right LR.

ML models, and more specifically RF, enhance prediction accuracy compared with traditional statistical methods like LR. This improvement is reflected not only in the higher accuracy of the RF model, but also in the fact that fewer predictive variables are required to achieve this performance. In fact, the use of fewer variables is another point in its favor because it is preferable to use models which are as simple as possible, thereby facilitating interpretation of the results. In addition, RF cartographic outputs (Figure 5) seem to be more realistic because this method has increased spatial variability and therefore higher discriminatory power in neighboring areas with different occurrence values. Moreover, BRT, SVM, and LR present high area concentrations in some of the classification intervals (low-mid values in BRT, low-high in SVM, and midrange values in LR), while RF seems to be more equally distributed, although most of the probability values are located in the first interval (Figure 4, Table 3). On the other hand, although the BRT model has similar performance to RF, its calibration and optimization involves more parameters, and therefore it is more difficult and time-consuming to compute. Finally, the authors consider that SVM is a less adequate method for predicting wildfire occurrences compared to the other proposed methods. This is mainly because its calibration is significantly more difficult, its optimization is too time-consuming, and its accuracy does not reach RF or BRT levels, remaining closer to LR. These findings are supported by the results reported in (Bar Massada *et al*., 2012), where the RF algorithm is proposed as the most adequate compared to logit GLM and Maxent models.

As for the explanatory variables, as in most human-dominated landscapes where anthropogenic ignitions surpass natural ignitions, in peninsular Spain, both human accessibility and population density are likely to be strong predictors of ignition risk (Bar Massada *et al*., 2012). However, although these factors make an important contribution in the study area –CDP or WUI (Galiana-Martin *et al*., 2011)–, other explanatory factors more related to agricultural activities and forest management also influence wildfire occurrence. More specifically, these involve negligence and accidents due to engines and machines working close to the forest areas (DAM), the use of fire in cleanup of harvest wastes and crop boundaries (WAI), and forestry protection policies (PA). Nonetheless, whereas DAM, CDP, WAI, and WUI are factors related to an increased ignition probability, PA intervenes in the opposite way, i.e., by decreasing ignition likelihood, because it is directly linked with the protection and conservation of landscape (Figs. 6 and 7).

In particular, DAM and CDP have proved to be the variables most closely related to fire occurrence in Spain. However, this high predictive power is also linked to the fact that these variables are continuous in nature, i.e., they have values in all the locations throughout the study area. Therefore, DAM and CDP can function as discriminatory variables in all cases, while the other predictors cannot. Note also that the continuous nature of DAM does not arise from there being machinery in all locations, but from the fact that it is obtained as a statistical value reported at the municipal level. Moreover, the influence of DAM should ideally be restricted to mechanized WAI because the focus is on ignitions in forest areas, and therefore the agricultural machinery must be in crop areas close to forest surfaces, i.e., being used for WAI. This fact is supported by the (non-collinear) interaction between DAM and WAI (Figs. 6 and 7), in which high values of probabilities are related to high values both of DAM and of WAI. On the other hand, CDP seem to have an inverse relationship with wildfire probabilities (Figs. 6 and 7), which means that a decrease in the demographic potential involves an increase in the predicted probability. This may appear strange or hard to understand, but might be related to the fact that in certain locations where nowadays the potential is lower than the initial potential, this initial potential has been almost completely overwhelmed. This indicates that the anthropic pressure in these areas has been significantly strong during the CDP time span (1991–2006), leading to an increased occurrence probability.

Table 3. Summary of area (km^2) distribution for each interval and model.

		RF	BRT	SVM	LR
Very low	0.0 – 0.2	91540	31798	172777	1435
Low	0.2 – 0.4	81069	139375	22401	136896
Medium	0.4 – 0.6	40375	51327	15054	98911
High	0.6 – 0.8	24438	29779	12088	15655
Very high	0.8 – 1.0	19437	4580	34539	3962

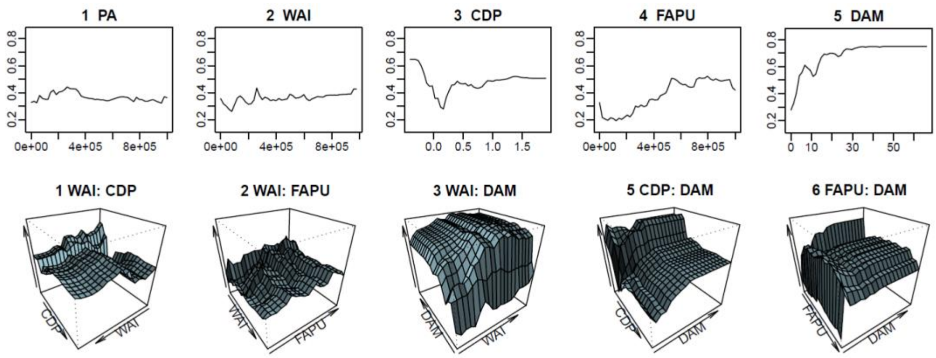

Figure 6. Response curves (top) and variable interactions (bottom) for predictive variables with RF.

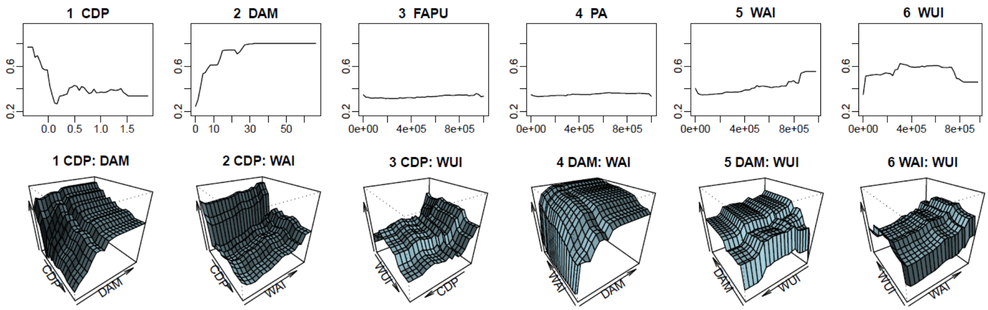

Figure 7. Response curves (top) and relevant variable interactions (bottom) for predictive variables with BRT.

5. Conclusions

ML models improve the prediction accuracy of traditional regression methods. Either RF or BRT models yield an improvement in accuracy over LR methods for wildfire occurrence assessment, according to AUC values. More specifically, the RF algorithm seems to be the best choice due not only to its higher accuracy, but also to the fact that fewer predictive variables are required to achieve this accuracy. In addition, its calibration is easier because it involves few parameters. Another advantage of RF is its cartographic outputs, which seem to be more realistic than those from other models due to RF's higher spatial variability and therefore greater spatial discriminatory power. This enables RF to provide a better reflection of variability in wildfire occurrence linked to heterogeneity of landscapes and human activities. SVM appears to be a less adequate method for predicting wildfire occurrences, mainly because its calibration is significantly more difficult, its optimization is too time-consuming, and its accuracy does not reach the levels of RF or BRT, remaining closer to LR. However, despite the similar predictive power of the proposed models, the resulting predictive maps were very different. This was especially noteworthy in the case of SVM, where the spatial patterns seem to be dichotomized, with probability values concentrated in two ranges close to the maximum and minimum values. Nevertheless, no single model or method can be considered as the perfect modeling tool (Elith *et al.*, 2006), and prediction of wildfire occurrences may benefit from using multiple approaches, yielding a range of predictions rather than a single map (Bar Massada *et al.*, 2012).

Regardless of the method considered, DAM and CDP have proved to be the variables most closely related to fire occurrence, although this result is partially due to the continuous nature of these variables and, in the case of DAM, to interaction with other predictive variables like WAI. In any case, fire occurrence in Spain is mainly related to the increase of human pressure on wildlands and to accidents or negligence in the course of agricultural work (Chuvieco *et al*., 2012).

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CHAPTER 7. UNCERTAINTY IN MODELING HUMAN-CAUSED WILDFIRE OCCURRENCE

This chapter presents the results of the uncertainty analysis of human-caused ignition data. The proposed method deals with the potential uncertainty that the inconsistences found in either location or source of fire history records may have in wildfire occurrence models.

The main goal is to determine which fire records should be accounted for when fitting historic wildfire occurrence models, and address its influence on both the predicted spatial patterns of ignition probability and the explanatory sense of wildfire driving factors.

Assessing the effect on fire risk modeling of the uncertainty in the location and cause of forest fires

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Abstract

Wildfire risk assessments in Spain usually make little or no reference to the uncertainty of the results due to ignition data quality, or the implications that this potential uncertainty may have on wildfire management decisions. In Spain the autonomous regions have been the competent authorities in forest management and environmental protection since 1978 and, therefore, responsible on defining the framework and criteria for wildfire classification and location. However, the lack of a common (national) standard has led to the establishment of different criteria for wildfire classification among the different autonomous regions, arising potential uncertainty on wildfire assessments and fire risk models based on this data. This work explores six scenarios based on the classification of fire ignition causes and location data, reported in the General Statistics of Wildfires database (EGIF), to address the potential uncertainty from the point of view of the variability in predicted ignition probability and the changes in its spatial patterns. The analysis is focused on analyzing the effects on human-caused wildfires by using Random Forest algorithms to predict the ignition likelihood and cluster and outlier analysis (hot and cold spot) to detect changes in the spatial pattern of probability. Results suggest that there is significant uncertainty both in predicted human-caused ignition and spatial pattern related to the ignition source and location of fire events compiled in the EGIF database. The accuracy of the predictions ranges from AUC values of 0.90, when considering most of the records of the database, to around 0.76 in scenarios characterized by using only known-caused allocated fire events.

Keywords: Uncertainty; wildfire; point location; ignition cause

1. Introduction

During the last decades, the Spanish forest fire authorities have encouraged the investigation of fire causes, which is decisive to better understand patterns of fire occurrence and improve fire prevention measures (Martinez *et al*., 2009). However, the 29% of the fire causes remain unidentified. According to Lovreglio *et al*. (2006), little is known about wildfire causes, which often are more diverse than what is assumed by the traditional classifications employed for statistical purposes. In face of the arising uncertainties, a better knowledge on spatial patterns of fire occurrence and their relationships with its underlying causes becomes a necessity to locate and make prevention efforts more efficient (Martinez *et al*., 2009). From a scientific perspective, improving decision quality in natural resource management begins with uncertainty management (Borchers, 2005). Uncertainty is essentially a lack of information; complete ignorance represents one end of the spectrum and perfect information (i.e., certainty) the other (Thompson and Calkin, 2011). However, viewing uncertainty as 'information about information' may be the first step in transforming a problem into knowledge (Bradshaw and Borchers, 2000).

The aim of this paper is to deal with the potential uncertainty linked to location and ignition cause of wildfires, with special attention to the human-caused fires in the Spanish peninsula. The analysis of human factors in forest fire is widely recognized as very critical for fire danger estimation (Kalabokidis *et al*., 2002; Martínez, 2009), especially in human-dominated landscapes where anthropogenic ignitions widely surpass natural ignitions, like the peninsular Spain (Amatulli *et al*., 2007; Chuvieco *et al*., 2012; Chuvieco *et al*., 2010). In Spain, fire events are recorded in the General Statistics of Wildfires database (EGIF). The EGIF database is one of the oldest 'complete' wildfire databases in Europe, beginning in 1968 (Vélez, 2001), though its data is not considered as completely reliable until 1988 (Martinez *et al*., 2009). The database is compiled by the Ministry of Environment, Rural and Marine affairs (MARM) using forest fire reports of the autonomous regions (Moreno *et al*., 2011). The autonomous regions have been the competent authorities in forest management and environmental protection since 1978 (article 148 of the Spanish Constitution, 1978), and therefore are responsible on defining the framework and criteria for wildfire classification and location. However, the fact that there is no common (national) directive on this topic has led to the establishment of different criteria among the different autonomous regions. A quick overview on the data collected in the database arises some inconsistences in the reported information. For instance, the proportion of unknown causes or the proportion of correctly located fire events (located with coordinates) differs from one region to another, becoming a potential source of uncertainty. This is especially important since research on forest fires in Spain is made from data collected in the EGIF database (Amatulli *et al*., 2007; Chuvieco *et al*., 2010; Chuvieco *et al*., 2012; de la Riva *et al*., 2004; Martinez *et al*., 2009; Padilla and Vega-García, 2011; Rodrigues *et al*., 2014; Rodrigues and de la Riva, 2014). Notwithstanding, the influence of uncertainty in historical fire data is scarcely considered (or at least not specifically addressed) and is mainly focused on location precision rather than ignition cause (Amatulli *et al*., 2006; Amatulli *et al*., 2007. Assessing the effects of uncertainty of Spanish ignition data is particularly interesting since it is a component of the wildfire information compiled European Forest Fires System Database (EFFIS), thus analyzing the effects of uncertainty at the Spanish level could be very helpful to understand wildfire patterns in the European scale, even more since Spain is the more fire-affected country within the European Union (Rodrigues *et al*., 2013).

In this work, we will explore six scenarios based on the classification of ignition causes and location data reported in the EGIF database to assess the potential uncertainty from the point of view of the variability in predicted ignition probability and changes in the spatial pattern of probability. The occurrence probability will be calculated using Random Forest (RF) algorithms (Breiman, 2001) whereas the changes in the spatial probability patterns will be addresses through local Hot Spot analysis. RF algorithms have proved to be a useful tool for wildfire modeling (Bar Massada *et al*., 2012; Rodrigues and de la Riva, 2014), improving the performance of traditional regression techniques (e.g. logit Generalised Linear Models). The comparison of the proposed occurrence scenarios is conducted from the point of view of the accuracy in the classification based on a k-fold procedure (Fielding and Bell, 1997) and according to the variation in variable importance (Breiman, 2001). On the other hand, Hot Spot methods are one of the most adequate for the analysis of large-scale fire occurrence patterns (Allgöwer *et al*., 2005). The analysis of the changes in the predicted ignition probability patterns in each scenario is carried out by cluster and outlier analysis through the Anselin's Local Moran's I (Anselin, 1995). Results suggest that there is substantial uncertainty both in predicted human-caused ignition and spatial pattern related to the classification and location of the fire events compiled in the EGIF database. The accuracy of the predictions ranges from AUC values of 0.90, when considering most of the records of the database, to around 0.76 in scenarios characterized by using only known-caused allocated fire events. The influence of the predictive variables is also variable. Regarding to the changes in the probability patterns, the mapping of cluster typology evidences high heterogeneity among the scenarios. However, the overall probability pattern seems to be similar from one scenario to another.

2. Materials and methods

2.1 Study area and fire data

The study area covered the whole peninsular Spain excluding the Balearic and Canary Islands as well as the autonomous cities of Ceuta and Melilla, due to the lack of data in those areas. Thus the total area of the study region was around 498 000 km^2. The fire events considered in this work are those occurred during the period 1988-2007. The year 1988 is considered as the beginning of the most reliable data recording for the EGIF database, whereas 2007 is the last year with complete information.

2.2 An overview to the EGIF database

The EGIF database is compiled by the Ministry of Environment, Rural and Marine affairs (MARM) using the forest fire reports from the autonomous regions. The database classifies each fire event following a hierarchy of criteria which first differences between known (K) and supposed (S) cause and then into the most likely ignition source (natural or human). In turn, the ignition source is classified according to six categories: natural (lightning; L), human (negligence, accident or arson; H), restarted fires (R) and unknown or unidentified fires (U). Ideally, only K fires should be considered when developing any kind of fire analysis as they appear to be the most reliable. However, an insight into the classification of fire events in terms of number of fires in each category (Table 1) reveals that the proportion of fires with a S cause is more than 73 % of the total number of fires in the period 1988-2007. Hence, by excluding S fires the majority of fire events are being discarded (Figure 1).

Table 1. Classification of fire events according to its ignition causes (number of fires).

	Lightning	Human	Unknown	Restarted	All
Known	6775	35443	30952	1957	75127
Supposed	7931	228694	44706	2420	283751
Total	14706	264137	75658	4377	358878

This classification system also influences the proportion of fires according to its ignition source. Attending to K source, L fires represent the 9% of the occurrence whereas H fires are only the 47%. The remaining fires mostly correspond to U sources. This proportion changes drastically when S cause fires are accounted for, decreasing the proportion of L fires to 4% and raising H fires to a 73%. However, this 73 % of H fires is still far from the 90% value usually reported for Mediterranean European Countries (San-Miguel-Ayanz *et al*., 2012a; San-Miguel Ayanz, 2009) and, particularly, for Spain (Martínez *et al*., 2009). This fact suggests that there is great amount of U fires potentially related to H ignition factors and thus, when excluding unknown fires in human-caused wildfire assessments, a significant part of the human occurrence is not taken into account. However, while U fires are quite important attending to national overall values, mapping the spatial distribution of these proportions uncovers the existence of high spatial heterogeneity, increasing the uncertainty on the data (Figure 1).

On the other hand, a second source of uncertainty is related to the location of fire events. In the EGIF database wildfires are located following to different procedures: (i) geocoding the location on the basis of a reference 10x10 km ICONA grid (used by the firefighting services for approximate location of fire events) and the municipality origin of the ignition; and (ii) georeferencing fire events using spatial coordinates. Again, the existence of coordinates should imply a precise allocation of the ignition points, however not all the fire events are georeferenced –only the 11% (Table 2)– and, as in the case of the ignition source, the proportion of fire events with coordinates varies from one region to another (Figure 2). This situation usually led to face the spatialization of the fire occurrence using geocoded location information (Amatulli *et al*., 2007; Chuvieco *et al*., 2012; Chuvieco *et al*., 2010; de la Riva *et al*., 2004; Martínez, 2009). On top of this, sometimes the assigned coordinates are incorrect. For instance, 2267 fires are located outside Spain, 23 are assigned a wrong UTM zone and 757 are located in the exact intersection of the ICONA grid (Table 2). This means that the 7.6% of the forest fires with spatial coordinates are mistakenly allocated.

Table 2. Number of fires with coordinates and wrong located wildfires.

	Located	Outside	Wrong zone	Intersects Grid	Total incorrect
Known	16435	962	18	347	1327
Supposed	23581	1305	5	410	1720
Total	40016	2267	23	757	3047

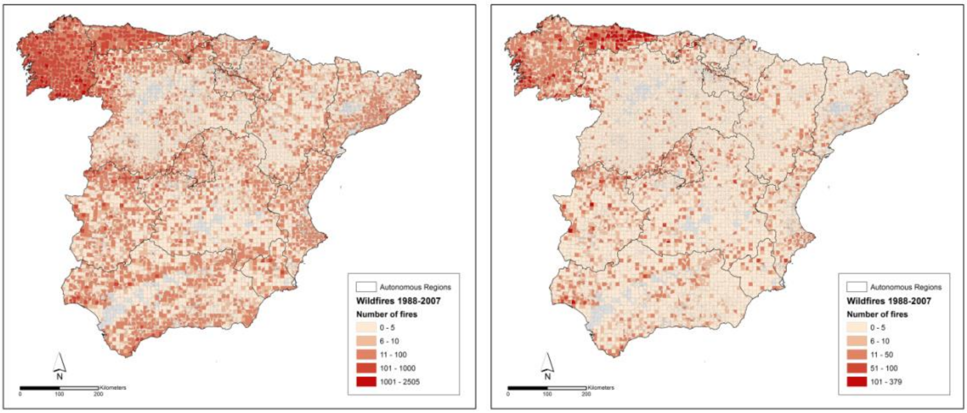

Figure 1. Spatial distribution of wildfires. Left total number of fires, right K fires.

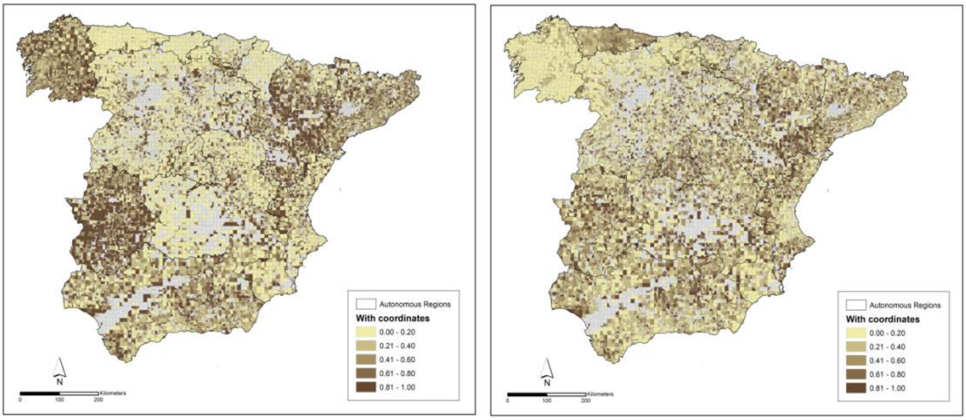

Figure 2. Spatial distribution of the proportion of points with coordinates. Total number of fires (left), fires with known cause (right).

2.3 EGIF scenarios

In this work, we explored six scenarios based on the classification of ignition causes and location data reported in the EGIF database. The proposed scenarios were constructed to simulate the most probable assumptions to select an occurrence sample for wildfire modeling purposes. The criteria followed to design the scenarios were based mainly in three parameters: certainty of the cause (known or supposed), certainty of the source (human or unknown) and presence of coordinates. Thus, the proposed scenarios are:

- Scenario 1: this scenario considers all human-caused fires, including both known and supposed cause, and a proportion of unknown fires according to the observed proportion of human-caused fires in the corresponding autonomous region.
- Scenario 2: this scenario considers all human-caused fire, including both known and supposed cause, excluding those fires with an unknown source.
- Scenario 3: this scenario considers all human-caused fire, but only those with known cause, excluding fires with a supposed cause, but including a proportion of unknown fires according to the observed proportion of human-caused fires in the corresponding autonomous region.
- Scenario 4: this scenario considers all human-caused fire, but only those with known cause, excluding fires with a supposed cause or an unknown source.
- Scenario 5: this scenario considers all human-caused fire, including both known and supposed cause located using coordinates, excluding

fires with an unknown source or those which are wrongly located according to Table 2.

- Scenario 6: this scenario considers all human-caused fire, but only those with known cause and located using coordinates, excluding fires with a supposed cause, an unknown source or those which are wrongly located according to Table 2.

2.4. Wildfire modelling

The assessment of human-caused wildfire occurrence was carried out using RF algorithms an ensemble classifier which uses decision trees as base classifiers (Breiman, 2001).

The dependent variable for each scenario was constructed by selecting human-caused fires (e.g. negligence, accident or arson). Then wildfires were spatialized through the assignment of each fire to its respective combination of ICONA grid, municipality and forest perimeter (Amatulli *et al*. 2007; Chuvieco *et al*. 2010,2012; de la Riva *et al*., 2004; Rodrigues *et al*., 2014;Rodrigues and de la Riva, 2014). This allowed the calculation of fire density maps at a spatial resolution of 1x1 km by overlaying the random point cloud with the Spanish 1x1 km UTM grid. The dependent variable was developed for each scenario by classifying the occurrence values into two categories: high occurrence (presence) in locations with two or more fires, and low occurrence (pseudo-absence or background) in locations with only one fire.

The explanatory variables were selected based on the experience of the authors in models at regional and national scales (Amatulli *et al*., 2007; Chuvieco *et al*., 2010,2012; de la Riva *et al*., 2004; Martínez, 2009; Rodrigues *et al*., 2014; Rodrigues and de la Riva, 2014. The predictive variables considered were: Wildland-agricultural interface (WAI), Wildland-urban interface (WUI), density of agricultural machinery (DAM), changes in demographic potential 1991-2006 (CDP; Calvo and Pueyo, 2008), protected areas (PA), forestry area in public utility (FAPU), forestry tracks (TRCK), railroads (RRDS) , power lines (PWR) and land use change 1991-2006 (LUC).

The comparison of the outputs (predicted probability of occurrence) from each proposed scenario was conducted from the point of view of the accuracy in the classification based on a k-fold cross-validation procedure (Fielding and Bell, 1997) and according to the variation in the variable importance (Breiman, 2001). In k-fold cross-validation, the original sample is randomly partitioned into *k* equal size subsamples (*k*=5 in this work). Each time, one of the k subsets is used as the test set and the other *k-1* subsets are putted together to conform the training set. The cross-validation process is then repeated *k* times (the folds), with each of the k subsamples used exactly once as the validation data. The k results from the folds then can be averaged to produce single error estimation (Bas Massada *et al*., 2012).

Variable importance assessment was carried out by summarizing the influence of the explanatory variables according to the increase in mean square error (IncMSE) and the increase in node purity (IncNP). IncSME is defined as the increase in the mean of the error of a tree in the forest when the observed values of this variable are randomly permuted in the out-of-bag samples. IncNP is measured using the Gini criterion, from all the splits in the forest based on a particular variable (Breiman, 2001). The variability in variable importance was addressed through the fluctuations in the ranks obtained by ordering the explanatory variables from more to less importance according to IncSME and IncNP.

2.5. Spatial variation in the ignition probability patterns

Changes in the spatial probability patterns were addressed through local Hot Spot analysis, one of the most adequate for this purpose (Allgöwer *et al*., 2005). The assessment of changes in the spatial pattern of predicted probability was based on the assumption that one of the key factors in wildfire management was guiding governments or responsible authorities through prioritization across fires and resources at risk. We considered that the identification of areas with high values of occurrence probability (Hot Spot) is linked to the identification of priority intervention areas.

The assessment of the changes in the predicted spatial pattern at each scenario is carried out by cluster and outlier analysis through the Anselin's Local Moran's I (Cluster and Outlier Analysis). This kind of analysis allows identifying and allocating Hot Spot areas as well as characterizes its typology of cluster. Given a set of weighted features, the Cluster and Outlier Analysis tool identifies clusters of features with values similar in magnitude. The tool also identifies spatial outliers. To do this, the tool calculates a Local Moran's I value, a Z score, a p-value, and a code representing the cluster type for each feature. The Distance Band or Threshold established for the cluster detection was 10 km. The results were mapped according to the significant detected cluster typology: Hot Spot (HH), Hot Spot surrounded by Cold Spot (HL), Cold Spot (LL) and Cold Spot surrounded by Hot Spot (LH).

3. Results

3.1. Predicted probability of occurrence

There is high variability (and therefore uncertainty) in predicted probability values among the six scenarios (Figure 3). In general terms, scenarios characterized by the use of both K and S causes, mainly scenarios 1 and 2, show high performance with AUC values stand above 0.9 (McCune *et al.*, 2002). Scenarios 2 and 3, where the occurrence used to construct the dependent variable only consider K causes are less accurate (AUC near 0.83) and values in the high probability interval (0.8 to 1) are almost inexistent. Scenarios where the ignition points are georeferenced using coordinates show the poorest accuracy and probability values are grouped in the first interval (0 to 0.2). In addition, the range of AUC values (difference between minimum and maximum value) shows a similar behavior, with lower values in scenarios 1 and 2, and increasing until scenarios 5 and 6. This means that the models fitted using a dependent variable constructed with both K and S causes are more stable and therefore more reliable. Table 3 summarizes the obtained AUC values. On the other hand, the same comportment is observed when considering the values of Max TPR+TNR. This parameter represents the best threshold to distinguish between presence/absence according to the maximum value of the kappa index i.e. the highest values of true positive rate (TPR) and true negative rate (TNR). In general terms, the higher the threshold the higher the accuracy of the model since it means that the model distinguish more efficiently between presence and background values.

The uncertainty observed in the probability values is also detected in the contribution of the explanatory variables for each scenario. Although the variability is higher in the importance ranks for IncSME than in IncNP (Table 4) there is a general tendency to promote always the same variables: DAM, CDP, WAI, PA and TRCK (the later only is observed in the IncNP). The rest of the variables are swapping ranks among the different scenarios.

Table 3. Summary of k-fold validation with k=5.

	S 1	**S 2**	**S 3**	**S 4**	**S 5**	**S 6**
Max AUC	0.908	0.904	0.838	0.844	0.845	0.784
Min AUC	0.906	0.899	0.827	0.829	0.821	0.746
Max TPR+TNR	0.341	0.324	0.125	0.146	0.123	0.062

3.2. Variation in spatial patterns of probability

Figure 4 shows the spatial distribution of the cluster characterization of the predicted probabilities. In the same way that occurs in the predicted probability of occurrence, there is high heterogeneity in the spatial pattern at each scenario. However, in this case a similar spatial pattern of cluster is observable among the six scenarios, with HH clusters in the northwest of the peninsula and the Mediterranean coast, HL clusters in Pyrenees and the central area of the peninsula and LH in the Cantabrian coast. However, the scenarios using known causes (scenarios 4 and 6) are presenting LL clusters in some regions of the Northwest of the peninsula which is not that would be expectable since this area presents the highest occurrence values (Figure 1).

Table 4. Importance ranks for the explanatory variables. Top IncSME, bottom IncNP.

	S 1	S 2	S 3	S 4	S 5	S 6	ranks
DAM	1	1	1	1	1	1	0
CDP	2	2	2	2	2	3	1
WAI	3	3	4	5	6	5	4
PA	4	4	3	3	3	4	3
FAPM	5	5	6	7	4	2	5
WUI	6	6	5	4	5	6	3
RAIL	7	8	7	6	7	9	4
PWL	8	9	9	8	9	8	2
LUC	9	10	10	10	10	10	2
TRCK	10	7	8	9	8	7	4
DAM	1	1	1	1	1	1	0
CDP	2	2	2	2	2	2	0
WAI	3	3	3	3	3	3	0
PA	5	5	5	5	5	5	0
FAPM	6	6	7	7	8	7	3
WUI	10	10	10	10	10	10	3
RAIL	9	9	9	9	7	8	3
PWL	7	7	6	6	6	6	2
LUC	8	8	8	8	9	9	2
TRCK	4	4	4	4	4	4	0

4. Discussion

Multiple sources of uncertainty remain with regard to modelling wildfire occurrence (Thompson and Calkin, 2011). Therefore there is a need to better understand how uncertainty and errors propagate through models (Sullivan, 2009). As little is known about wildfire causes (Lovreglio *et al*., 2006) many authors have chosen to deal globally with human-caused fires, avoiding uncertain specifications of causes, and have been able to derive useful recommendations for management (Stephens, 2005). Nevertheless, using a coherent framework informs management authorities by facilitating the identification of potential sources of uncertainty and the quantification of their impact.

In Spain, near a 29% of the fire events have an unidentified cause and the remaining 71% are not fully reliable because the existence of certain degree of uncertainty regarding ignition source and location. This uncertainty is firstly detected while analyzing and mapping fire data; and secondly when occurrence data is used for wildfire modeling. Uncertainty is affecting both to the predicted probability values as well as the spatial pattern of probability.

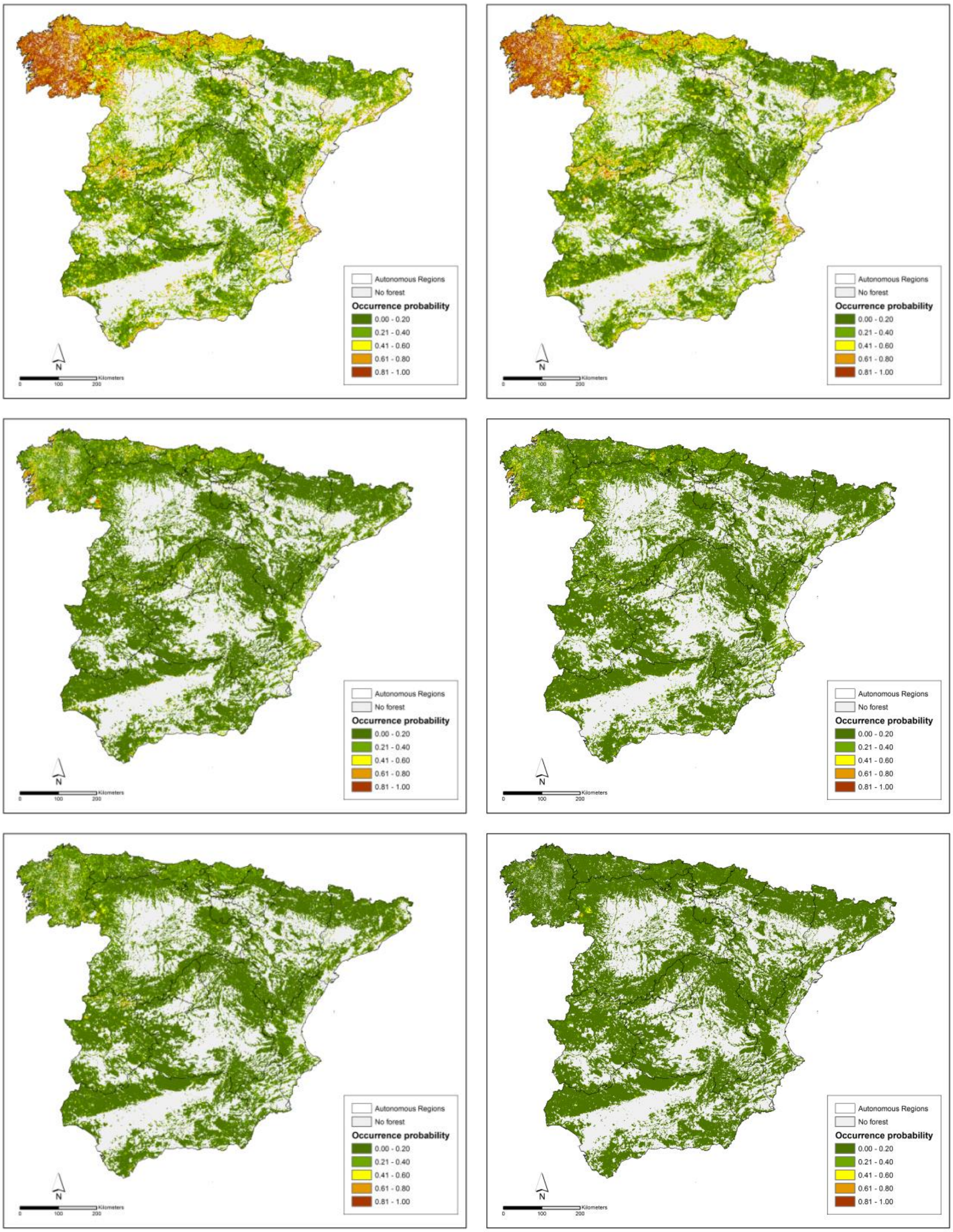

Figure 3. Spatial distribution of the predicted probability values. Scenarios are ordered consecutively left-right-top-bottom

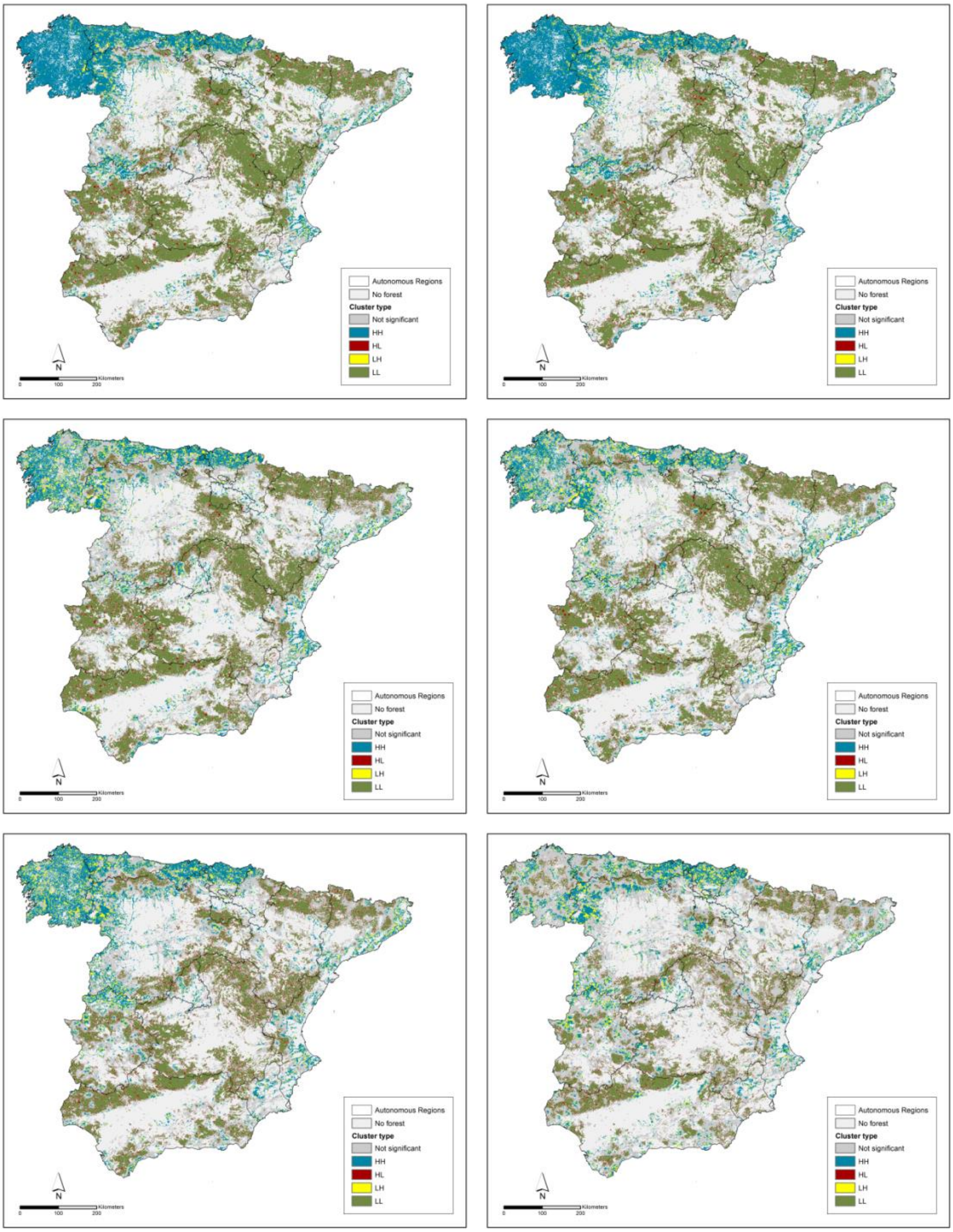

Figure 4. Spatial distribution of the cluster type. Scenarios are ordered consecutively left-right-top-bottom.

According to the results may vary greatly depending on to the assumptions made when constructing the dependent variable. Results suggest that the scenarios based on the consideration of all causes (K and S) as well as a proportion of the fires with a U source are more accurate, with AUC values above 0.9.We believe that this is mainly because when considering the whole occurrence, the dependent variable is less ‘spatially biased’ since there is no partial criterion to leave out a particular set of fire events and, thereby, the spatial pattern should be closer to reality. It is expectable that the scenario with the less uncertainty in its occurrence data, i.e. a scenario with known causes and (scenario 6), would be the most accurate. However, the fact that there are differences in the proportions of unidentified and allocated fires within the Spanish peninsula is harming the quality of the data.

In addition, there is also uncertainty in the contribution/importance of the predictive variables. This might be a big issue in research works aiming to determine the factors that are explaining wildfire occurrence because the assumptions made when constructing the dependent variable are influencing the contribution of the explanatory variables.

Regarding to the predicted probability spatial pattern, although the variability is lower than the detected in the case of the predicted probability, it is still great. As in the case of the probability of occurrence, scenarios based on the consideration of all causes (K and S) including a proportion of the fires with an unidentified source seem to be the most realistic approach.

5. Conclusions

The lack of homogeneous criteria among the autonomous regions on forest fire management is a potential source of uncertainty for wildfire risk assessment which is affecting both the predicted probability values as well as the spatial pattern of probability. This is especially significant since research on forest fires in Spain is made from data collected in the EGIF database (Amatulli *et al*., 2007; Chuvieco *et al*., 2010, 2012; de la Riva *et al*., 2004; Martinez *et al*., 2009; Padilla and Vega-García, 2011). Although some studies have been able to derive useful recommendations for management avoiding uncertain specifications of causes (Stephens, 2005), addressing arising uncertainty in occurrence data can help improve assessments.

The spatial distribution of wildfire ignition greatly varies depending on the assumptions made when considering the ignition cause and source, leading to different predictions. However, it is possible to determine the best scenarios for modeling wildfire occurrence or risk. According with our results the best choice is consider both K and S causes with a proportion of forest fires with unknown source. There is a big amount of unidentified fires potentially related to a human ignition source and thus, when excluding unknown fires in human-caused wildfire assessments, a significant portion of the occurrence is not accounted for. Considering this supposedly human-caused occurrence reduces the spatial biased conducting to more robust and reliable predictions. Uncertainty is also affecting the contribution of the explanatory variables. Results suggest that DAM, CDP, WAI and PA are the least sensitive variables to variations in the spatial distribution of the occurrence.

Acknowledgements

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CHAPTER 8. QUANTITATIVE ASSESSMENT OF ECOLOGICAL VULNERABILITY

This chapter summarizes the results, discussion and conclusions of the application of the proposed method for quantitative assessment of ecological vulnerability to the case study of mainland Spain. The method is based on an inductive map algebra procedure that integrates geospatial information regarding plant species characteristics and environmental conditions into a spatial explicit recovery time value.

A method for regional scale assessment of vegetation recovery time after high severity wildfires: case study of spain
(Appendix E)

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Abstract
This study aims to develop a method to estimate the recovery time of plant communities after high severity wildfires. The designed methodology is based on map algebra and a geographical information system, which enabled calculation of the approximate time required to restore vegetation to conditions similar to pre-fire regarding plant height and canopy cover. The methodology considered firstly the vegetation in the territory, characterized by the structure of the dominant plant community (tree, shrub, or grassland) and its regeneration strategy (resprouter or seeder); and secondly two of the main factors determining recovery time, water availability and soil loss. We also considered the influence of observed rainfall trends over the past 50 years on these latter two factors. The methodology was applied to Spain to test its performance. The results suggest a period of 2 and approximately 100 years for grassland communities and tree communities with low germination, respectively. There are significant differences in plant communities between the two biogeographic regions (Euro-Siberian and Mediterranean) as well as within each community, directly linked to variability in terrain and climatic conditions.

Keywords: GIS; plant communities; recovery time; wildfire.

1. Introduction
Forest fires have traditionally been linked to the Mediterranean climate due to the coexistence, in some months of the year, of high temperatures and low rainfall (Camia and Amatulli, 2009). The indigenous vegetation has lived with fire for millennia, and thus it is not an extraneous factor to the Mediterranean environment or, more specifically, to peninsular Spain (Pausas and Vallejo, 1999; Pyne, 2009; Wagtendonk, 2009). However, recent changes in socioeconomic models and climatic patterns have significantly affected the historical fire regime in Southern Europe (San-Miguel *et al*., 2012a; González *et al*., 2010), with potential damage far greater than traditionally experienced (Bodí *et al*., 2012; Bowman and Boggs, 2006; Meyn *et al*., 2007; Pausas and Vallejo, 1999). In Spain, the total area burned (with an annual average of over 125 000 hectares from 2000 to 2008, but almost 250 000 hectares per year

from 1980 to 1989; Schmuck *et al*., 2009) has decreased in recent years, while the number of fires has increased (18 150 compared to 15 300 in the corresponding periods; San-Miguel *et al*., 2012a; Schmuck *et al*., 2009). Furthermore, the chances of suffering an especially dramatic fire season, as in several countries in the last decade as a result of extreme heat waves (Rebetez *et al*., 2006) (Spain, 2000 and 2005; Portugal, 2003 and 2005; Greece, 2007; Australia, 2009; Russia, 2010) appear to be increased (Allen *et al*., 2010; Camia and Amatulli, 2009; San-Miguel *et al*., 2012b; van Mantgem *et al*., 2009) and are likely to occur more frequently in the coming decades (Seidl *et al*., 2011). The main trends of degradation induced by fire in the medium and long term may include permanent changes in the floristic composition of the plant community, reduction of vegetation cover, biomass loss, and alteration of landscape patterns. Forest fires can also induce long-term changes in floristic and physiognomic parameters of vegetation through their impact on the physical and chemical properties and nutrient availability of soil (MMA, 2006; Vallejo *et al*., 2009). After the burning of vegetation, the contribution of ash to the soil temporarily increases the availability of some nutrients (P, Mg, K, Ca, Na). This initial fertilization depends on the severity of the fire and the amount of biomass (fuel) prior to the fire. However, other nutrients such as nitrogen may volatilize or be washed away as a result of wind or water erosion post-fire (Neary *et al*., 2009; Shakesby and Doerr, 2006). In addition, the loss of vegetation cover after fire increases surface erosion because the bare soil is exposed to raindrop impact and surface runoff, especially in the first months after burning (Giovannini *et al*., 2001; Inbar *et al*., 1998).

Therefore, it is necessary both to improve our early warning systems and to encourage the assessment of potential environmental damage (Chuvieco *et al*., 2010, 2012), as such natural and semi-natural ecosystems provide many important functions (or ‘services’) of economic, cultural and aesthetic value to human societies (Costanza *et al*., 1997). In this sense, assessment of vegetation response after fire can support governments' forestry policies, forest service activities, and fire-risk modeling. This is particularly so since the lack of spatial data on this subject has to some extent hindered natural resources management agencies from identifying priority areas for adaptation measures (Brooks *et al*., 2006; Hannah *et al*., 2002). This is especially true in Mediterranean ecosystems where fire is the main natural disturbance, exerting a decisive role on the structure and dynamics of plant and animal communities (Arianoutsou *et al*., 2011; Bajocco *et al*., 2011; Cerdà and Doerr. 2010; di Castri and Mooney, 1973; Gill *et al*., 1981; Naveh 1975; Trabaud and Lepart, 1980).

This study focuses on the development of a method to assess the time required for vegetation to reach a state approximating pre-fire with similar levels of vegetation cover, restoring its physiognomic properties on regional scales, assuming that the dominant community species remain the same after fire (Broncano *et al*., 2005). Here vegetation means more specifically the dominant plant community. Other methodologies for assessing vegetation response to forest fires in Mediterranean-type ecosystems have already been designed. Bisson *et al*. (2008) presented an index of plant community resilience to fire. Arianoutsou *et al*. (2011) evaluated the post-fire resilience of Pinus halepensis in Cape Sounion National Park, Greece, using GIS and multi-criteria analysis. De la Riva *et al*. (2008), Alloza *et al*. (2006), and Duguy *et al*. (2012) produced a qualitative index of ecological vulnerability to forest fire in Mediterranean environments. In any case, these methods provide qualitative results; however, while they may be useful in some areas for territorial management, they are inadequate for other kinds of analyses such as quantitative assessment of fire-induced economic losses due to interruption of environmental services (e.g. timber, hunting, and mushroom gathering). For these, it is essential to know the period during which that service was lost (Román *et al*., 2013).

To overcome this limitation our methodology follows a different approach, estimating the post-fire recovery time of vegetation by integrating some of the major factors and processes influencing vegetation development after fire: the pre-fire structure of the dominant plant community (grassland, shrubland, or trees), the post-fire regeneration strategy of the dominant plant community (resprouter or seeder) (Baeza and Roy, 2008), water availability for vegetation development (from rainfall), and soil loss as a consequence of loss of canopy cover. The first two (vegetation structure and regeneration strategy) are intrinsic characteristics of the plant species, and are used to define the post-fire response capacity of plants (Alloza *et al*., 2006; de la Riva *et al*., 2008). The dichotomy of resprouters versus seeders is an important factor when analyzing the consequences of fire for vegetation (Pausas *et al*., 2008). The latter two (water availability and soil loss) are parameters that mainly depend on the characteristics and temporal evolution of the climatic conditions (Certini, 2005), influencing plants by modifying the amount of available nutrients and water or soil chemical composition (Shakesby and Doerr, 2006). Climatic conditions and soil loss are considered key parameters when modeling relationships between wildfire and vegetation (Daly *et al*., 2000; Lenihan *et al*., 2008). To include the influence of possible changes in the climatic conditions, the temporal evolution of seasonal rainfalls is considered. Our method focuses on obtaining a quantitative result, easily transformable into a qualitative one. However, it is not intended to provide a categorical recovery time, since our main goal is to develop a methodological approach for its assessment. We are fully aware that the vegetation recovery time may vary to a greater or lesser degree depending on local characteristics, e.g., the type and characteristics of vegetation, climatic conditions or terrain (Baeza *et al*., 2007; Keeley, 2009). Consequently, in this study we intend to supply an indicative result, though a more accurate one than provided by qualitative analysis. A method for validation of the results, based on monitoring the post-fire evolution of NDVI in fire-affected plant communities, is also proposed and discussed.

2. Materials and methods

The study area covered the whole of peninsular Spain, thus excluding the Balearic and Canary Islands as well as the autonomous cities of Ceuta and Melilla. The study region was further restricted to forested areas, meaning that urban, agricultural, and inland water zones were also excluded from the assessment. No data are reported for these areas or shown on the maps.

The methodology for estimating the post-fire vegetation recovery time (RT) is based on calculating the regeneration time of plant communities. An initial RT (recovery time under optimum conditions, RTOC) is assigned according to the dominant plant communities' structure (grassland, shrubland, or trees) and regeneration strategy (resprouter or seeder). The increase in time is then calculated by introducing the influence of plant species growth constraints (PSGC): water availability from annual rainfall, soil erosion due to loss of protective vegetation cover, and seasonal rainfall trends, which influence both water availability and soil loss mainly after the fire. The influence of water availability and soil erosion is introduced as a weight factor of RTOC. In turn, seasonal rainfall trends, specifically winter and summer trends, are introduced by weighting water availability and soil loss. RTOC is assigned based on experts' criteria supported by a literature review (detailed later), in a scenario of optimal conditions for vegetation development. This means that we consider that the recovery process takes place with no constraining factors for vegetation development, such as water and/or nutrient availability, chemical alteration of the soil, or fire recurrence. Figure 1 shows the process followed for calculation of the recovery time.

The following subsections describe in detail each stage of this methodology, beginning with the assignment of the RTOC, and then the PSGC. Finally, we present the method for calculating the vegetation RT and a validation procedure to test the performance of the method. The methodology was implemented in a GIS environment using map algebra and spatial analysis tools to calculate and map the recovery time. The spatial resolution of the input parameters was 1 km × 1 km, except for the rainfall trend maps which were 15 km × 15 km.

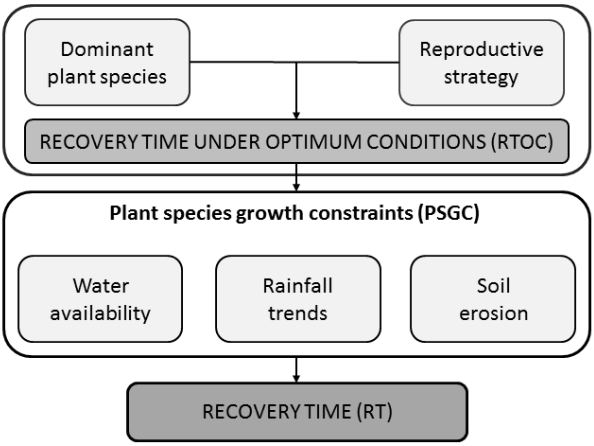


Figure 1. Methodology for RT calculation.

1.1. RTOC

Some plant species are better adapted to fire than others and either better resist the impacts of fire or recuperate more quickly, depending on the regeneration strategies and horizontal and vertical continuity (Baeza and Roy, 2008). Initially, the RTOC assessment is made from lists of dominant plant species in the Forest Map of Spain (MARM 1997), giving an individual characterization, in terms of their structure and regeneration strategy, of more than 500 species. As stated above, the characterization is carried out assuming that the vegetation recovery process occurs under optimal conditions. Plant characterization is based on the experience of the authors (de la Riva *et al*., 2008; Duguy *et al*., 2012) and several studies of post-fire vegetation and response (e.g. Baeza and Roy, 2008; Barbéro *et al*., 1998; Buhk *et al*., 2007; Martinez, 2005; Pausas *et al*., 2004; Tárrega and Luis-Calabuig, 1989; Trabaud, 1990, 1998, 2002; Vera de la Fuente, 1994). It should be noted that we did not find all the information required for the characterization of all species in Spain; as a result, several species are classified according to the authors' criteria alone. Accordingly, the initial time assigned is not intended to be a categorical value, since this could vary significantly depending on the local characteristics of each site and the influence of some parameters, as is the case for local topography (slope or aspect), climatic conditions, steppe vegetation or open scrub, climatic aggressiveness from heavy rainfall and steep slopes (Baeza *et al*., 2007; Keeley, 2009). Table 1 shows the resulting combinations of structure and regeneration strategy, the RTOC assigned to each as well as representative plant species for each vegetation structure and regeneration strategy category. Figure 2 shows RTOC spatial distribution in Spain.

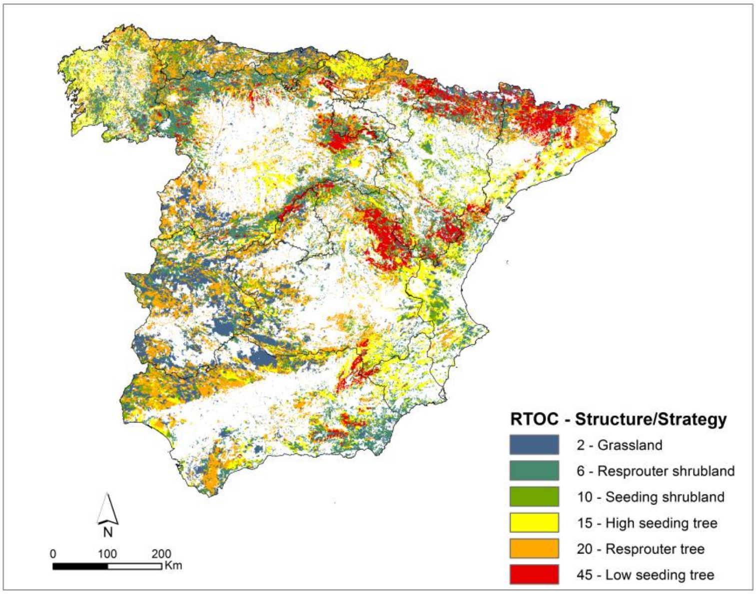


Figure 2. Spatial distribution of RTOC.

1.2. PSGC

This section describes the process followed to obtain the values of PSGC due to both water availability and soil loss.

Table 1. Approximate RTOC depending on vegetation structure and regeneration strategy and representative examples of plant species.

	Time (years)	Representative species
Grassland	2	-
Resprouter shrubland	6	*Buxus sempervivens, Quercus coccifera*
Seeder shrubland	10	*Juniperus thurifera, Ulex parvilflorus*
Resprouter tree	20	*Quercus robur, Quercus ilex, Quercus faginea*
High seeding tree	15	*Pinus halepensis, Pinus pinaster*
Low seeding tree	45	*Pinus sylvestris, Pinus nigra*

2.2.1 Water availability

The increase in RTOC depending on water availability in the area (F_w) is derived from the precipitation data reported in the Vegetation Series map of Spain (Rivas and Gandullo, 1987). This map was initially developed to delineate areas of recognized vegetation units (also referred to as series) to determine the great diversity of forest ecosystems in Spain. However, each of the different series was also assigned a typical rainfall category (arid, semiarid, dry subhumid, humid, and hyper-humid) based on annual local precipitation. This allows the assessment of water availability by grouping these rainfall categories, subsequently recoding them to a numeric value of the increase ratio

(F_w) of the RTOC. This map is particularly suitable for achieving the objectives of this research, since orographic parameters and bioclimatic characteristics were considered in the process of mapping the vegetation series. Table 2 and Figure 3 show the correspondence between typical rainfall intervals and the ratio of increase (assigned following the criteria of the present study) and rainfall distribution.

Table 2. Water availability, post-fire erosion rates, and corresponding RT increase ratios.

Rainfall category	Precipitation (mm)	F_w	Post-fire erosion rate (E_f) (ton ha^{-1} year^{-1})	F_e
Hyper-humid	> 1600	0.000	< 0.04	0.000
Humid	1000–1600	0.075	0.04–0.13	0.075
Sub-humid	600–1000	0.150	0.13–0.36	0.150
Dry	350–600	0.600	0.36–0.86	0.225
Arid-Semiarid	< 350	1.200	> 0.86	0.325

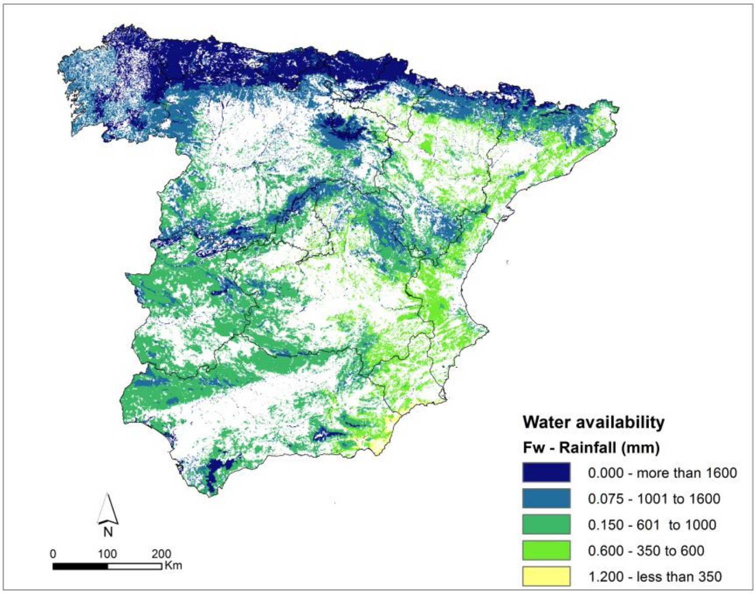


Figure 3. Spatial distribution of annual rainfall and water availability increase ratio.

2.2.2. Post-fire soil erosion

Soil erosion is another major negative outcome of forest fires, particularly in the Mediterranean region (San-Miguel *et al*., 2012b). Within Europe, the risk of water-driven soil erosion is particularly high in the Mediterranean region where autumn rain storms often follow summer wild fires (Pausas and Vallejo, 1999). The susceptibility of a burnt area to soil erosion depends on the intensity of the fire and the degree to which the vegetation cover is removed (San-Miguel *et al*., 2012b). The evaluation of the

RT increment as a function of soil loss (F_e) was carried out using a spatial analysis of the distribution of soil erosion in post-fire conditions. To this end, the Pan-European Soil Erosion Risk Assessment model (PESERA, Kirkby *et al*. 2004) was used. PESERA is a spatially distributed model at 1x1 km resolution for quantification of water soil erosion. A model of erosion at regional level is necessary to serve as a starting point for modifications to the RTOC. PESERA, which is more detailed than models such as USLE (Wischmeier and Smith, 1960), includes information on several soil parameters, such as soil erodibility, readily available soil water capacity, and crustability in order to define soil water storage capacity. The PESERA model was developed to provide spatial information on erosion risks at European level using a simple conservative erosion model, which is broken down into components that depend on climate, vegetation, soil factors, and topography. The physical model is based on a one-dimensional soil–vegetation–atmosphere transfer type scheme for surface hydrology, coupled where appropriate to a dynamic model for generic vegetation growth and/or remotely sensed land-use data (Kirkby *et al*., 2004). This model can be used as a tool at regional level, comparable to others such as the USLE (Wischmeier and Smith, 1960). Model results are validated at a basin scale and compared with data obtained using different methods of erosion measurement. More specifically, PESERA validation is based on comparison with erosion plot (40 m^2), small catchment (0.01-1 km^2), and reservoir (1-100 km^2) data (Cerdan, 2003; Tsara *et al*., 2005; Van Rompaey *et al*., 2003). These data have been used primarily to modify the pedo-transfer functions, particularly for soil erodibility.

In the current study, the Spanish subset of the European-scale PESERA map was used, although modifications have been made relating to the erosion processes that follow severe wildfires. An extensive literature review indicated great variability in the effect on erosion of plant cover loss resulting from fire. The erosion rate (tons ha^{-1} $year^{-1}$) increments range from an increase of 18.6 (Soto *et al*., 1994; Soto and Diaz-Fierros, 1998) to 5200 (Shakesby *et al*., 1994, 2002; Shakesby, 2011) times the initial erosion rate. Given the very considerable heterogeneity of these values, due to differences both in ecological conditions where the experiments were carried out and in the design and techniques used (erosion traps, rainfall simulations, erosion plots, etc.), we selected the ERMiT model (Robichaud *et al*., 2006) to modify the PESERA pre-fire erosion rates. The ERMiT model integrates information on climate indicators, soil (texture), topography (slope and slope length), plus the type of vegetation affected and the severity level of the fire, thus allowing simulations to assess fire-caused increases in erosion rates. The model uses a probabilistic approach that incorporates temporal and spatial variability in weather, soil properties, and burn severity for forests, rangeland, and chaparral hill slopes. ERMiT allows calculation of the percentage increase in the pre-fire erosion rate (PESERA) in several vegetation communities, which are characterized in terms of climate, soil, and topography indicators, given a specific fire severity (high severity in our case). The ERMiT model simulations were carried out in several locations considered representative of each Spanish bioclimatic region (derived from Rivas and Gandullo, 1987) and where climatic data were available (four locations in the Euro-Siberian region – A Coruña, Oviedo, Santander, and Bilbao – and five in the Mediterranean – Madrid, Barcelona, Valencia, Seville, and Zaragoza). This enabled us to develop different scenarios covering several combinations of vegetation structure, slope, and fire severity. The increase factor was calculated for each location, dividing the erosion rate obtained for a high severity fire by the pre-fire erosion rate. These quotients were calculated for each combination of vegetation structure, slope, and bioclimatic region and expressed as an average value. This process was carried out using the results provided by ERMiT for the first two years after a fire. Experimental data and measurements demonstrated that soil losses are significantly higher after a forest fire, being quickly reduced after 2 to 4 years (Cerdà and Doerr, 2005). The average increase factors obtained for the two years after burning were summarized into a single value to calculate the amount of erosion increment as consequence of wildfires. Table 3 summarizes the average increase factors.

Table 3. Increase factor of soil erosion by bioclimatic region, vegetation structure, and slope.

Structure	Slope (%)	Mediterranean Region	Euro-Siberian Region
	< 15	1.80	1.95
Forest	15–45	1.70	1.75
	> 45	1.70	1.75
	< 15	1.80	1.75
Shrubland	15–45	1.80	1.75
	> 45	1.80	1.80
	< 15	1.80	1.70
Grassland	15–45	1.75	1.75
	> 45	1.70	1.75

Once the erosion rates were corrected to take account of the effect of losing the protection of the vegetation cover as a result of fire, the obtained values were reclassified into five intervals (by quantiles) to assign the RTOC increase ratio (assigned following the criteria of the present study). Table 3 and Figure 4 show the soil erosion increment factor and its spatial distribution.

The soil erosion rates reported in the PESERA model were then modified, including the factor of erosion increase obtained from the simulation with ERMIT, using the following equation:

$$E_f = \sum E_{Pre} F_{resy}$$

where E_f is the corrected erosion rate (Mg ha^{-1} year^{-1}), E_{Pre} is the original erosion rate reported in the PESERA model, r is the bioclimatic region, e is the vegetation structure, s is the slope interval, and F_{re} is the soil erosion increase factor in bioclimatic region r and year y.

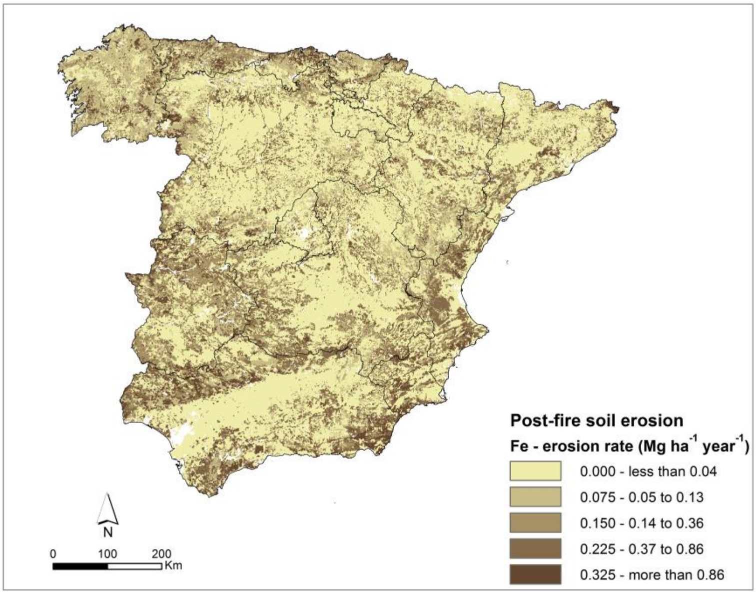


Figure 4. Spatial distribution of post-fire erosion rates and increase ratio.

2.2.3. Rainfall trends

Climate trends are a key factor in vulnerability assessment (González *et al*., 2010). Most climate change predictions imply increased air temperatures and less summer rainfall for the Mediterranean basin (Hertig and Jacobeit, 2008; Schröter *et al*., 2005). Adverse climatic conditions (i.e., dryer conditions) in many of the areas affected by fires may have caused lower rates of post-fire vegetation recovery (San-Miguel *et al*., 2012a). Hence, the observed changes in temperature and precipitation provide indicators of the potential change of the biome of an ecosystem (González *et al*., 2010). In this context, using observed climate data accounts for the impact of climate change that has already occurred (González *et al*., 2010).

Rainfall trends were included in the RT calculation as a weighting factor of the PSGC. In this sense and in general terms, we consider that a decrease in precipitation (negative rainfall trends) should imply a decrease in water availability; thus, the influence of a lack of water increases (San-Miguel *et al*., 2012a). A similar behavior is expected in the case of soil erosion, though in the opposite direction: here an increase in precipitation (positive rainfall trends) should increase its effect on the RT (Pausas and Vallejo, 1999), if water erosion is considered the main erosion mechanism. To include this in the recovery time model, we used the reported rainfall trends in de Luis *et al*. (2010). In that study, the spatial variability of seasonal precipitation regimes in the Iberian Peninsula were calculated for a temporal period of observations of 50 years from 1946 to 2005, using the Mann–Kendall test. The spatial variability of the seasonal trends is characterized according to the sign and significance level of the observed trends. As the rainfall trends were calculated only at seasonal level, we used winter trends to weight water availability, considering this to be the most effective season for plants to capture water, due to low potential evapotranspiration. We used autumn trends for soil erosion weighting, as this is the most critical season due to the dryness of the soil following summer (Pausas and Vallejo, 1999), the decreased vegetation cover from the loss of leaves in deciduous communities, and torrential rains (de Luis *et al*., 2010). It should be noted that when considering seasonal trends instead of annual trends we are including in the analysis of intra-annual variability of the precipitations. Rainfall trend weights ranged from 1 in locations where there was no significant trend (p-value < 0.70) to 2 in locations with significant with p-value > 0.99. Figure 5 shows the spatial distribution of winter (T_w) and autumn (T_a) trends, respectively, the significance levels, and their corresponding PSGC weights.

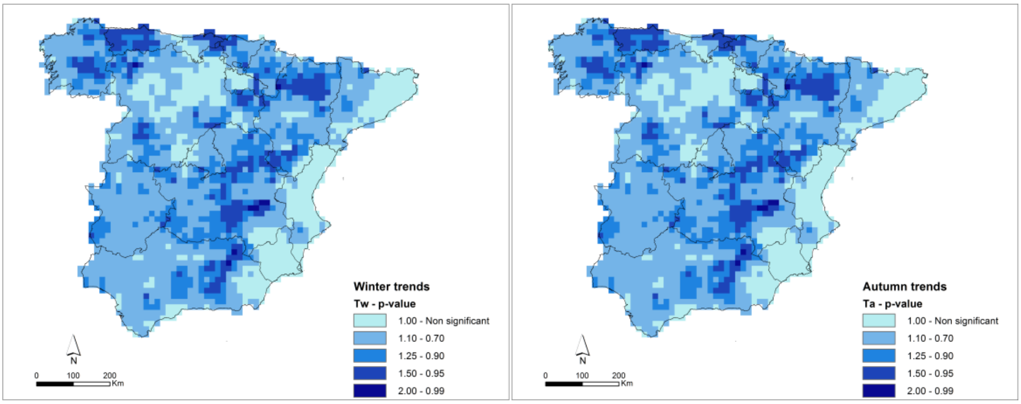


Figure 5. Spatial distribution of seasonal rainfall trends and their increase ratio. Negative winter trends (left) and positive autumn trend (right).

3. RT

The RT was calculated as the sum of RTOC and the time increase from the PSGC:

$$RT = RTOC + T_{Fw}T_w + T_{Fe}T_a$$

where T_{Fw} is the time increase from water availability, T_w is the winter rainfall trend weight, T_{Fe} the time increase from soil loss, and T_a is the autumn rainfall trend weight.

Once again, it should be emphasized that this RT is not a categorical value, rather an indication of the period needed to return to pre-fire conditions, since the main objective of this work is to develop a methodological framework to assess recovery time.

4. Model validation

Validation is often a complex issue in ecological models (Rykiel, 1996). Here we suggest a validation procedure based on the previous work by Perez-Cabello (2002) and Pérez-Cabello and Ibarra (2004). These works proposed the multi-temporal monitoring of changes in NDVI (Normalized Difference Vegetation Index) in burned plots as a tool for assessing the reconstruction process of various forest communities. In the present work we applied the same method to determine an approximate time span for the validation of the RT values. The NDVI has been the most frequently used tool for monitoring, analyzing, and mapping temporal and spatial post-fire variations (Díaz-Delgado *et al.*, 2002, 2003; Riaño *et al.*, 2002; Viedma *et al.*, 1997). NDVI is also used as a validation instrument in analyses similar to that in this paper (Bisson *et al.*, 2008).

The NDVI is related to changes in the amount of green biomass, pigment contents and concentrations, and leaf water stress (Gong *et al.*, 2003), that is why it emphasizes the regeneration process of burnt areas more clearly than the respective spectral signatures (Viedma *et al.*, 1997; Riaño *et al.*, 2002). However, NDVI responds more to changes in leaf area than to changes in the overall biomass (Henry and Hope 1998), reaching saturation levels at high LAI (leaf area index) values (Wang *et al.*, 2005). Therefore, tracking post-fire vegetation recovery using NDVI should be limited to the most recent development stages – 10 to 20 years after fire – as it registers information related to the vegetation cover (Tanase *et al.*, 2011).

The validation methodology was based on monitoring the temporal evolution of the recovery process in burned plots by measuring the NDVI values for several plant communities affected by severe wildfires during several years after burning. NDVI values were calculated from Landsat TM images, previously corrected geometrically and radiometrically to ensure the consistency of the results. Cloud spots were deleted from each image to avoid undesired radiometric effects. The calculated NDVI values were compared with the pre-fire conditions (also characterized in terms of NDVI) to determine an approximate time for plant recovery. The method has been applied to seven plant communities (*Pinus sylvestris, Pinus nigra, Pinus halepensis, Quercus ilex, Quercus faginea, Quercus coccifera* and *Buxus sempervirens*) affected by high severity (dNBR > 660; normalized burn ratio; Cocke *et al.*, 2005) wildfires in 1985 and 1986 in the Huesca Pyrenees region (see supplementary material). These plant communities are considered as representative examples of vegetation structure and regeneration strategy categories (see Table 1). Moreover, the analysis region is particularly suitable for validation since it is located in a transition area from Mediterranean to Euro-Siberian regions and, therefore, plant communities in this area are a representative example for our purposes. Ten examples of affected plant communities, four in 1985 and six in 1986, compose the validation sample. The NDVI data for 1985 was obtained from Perez-Cabello (2002) who calculated the NDVI for burned communities of *Pinus sylvestris, Quercus ilex, Quercus faginea*, and *Buxus sempervirens* since 1984 (pre-fire) until 1997. NDVI values for 1986 fire-affected communities were calculated from fifteen Landsat TM images during the period 1984 to 2007 in *Pinus sylvestris, Pinus nigra, Quercus ilex, Quercus faginea, Quercus coccifera,* and *Buxus sempervirens* communities. The recovery time span was determined by comparing post-fire and pre-fire NDVI values, considering the affected community as recovered from the fire disturbance when the post-fire NDVI is higher than the pre-fire one. However, in those cases where the affected communities did not reach pre-fire NDVI values during the analysis period, a logarithmic profile evolution curve was projected from the observed NDVI data to establish a recovery time span. To complete the validation procedure, predicted RT values were compared with the outputs from the NDVI monitoring.

5. Results

Here we present the results obtained from applying the proposed methodology to the mainland Spain, as well as the main outputs from the model validation.

5.1. Recovery time

The main results obtained from applying the proposed methodology in mainland Spain is the RT map (Figure 6). A statistical summary of the results is also given in Table 4. This statistical summary is constructed by using a zonal statistics algorithm, with RT values, using as zonal layer the categories from Figure 2.

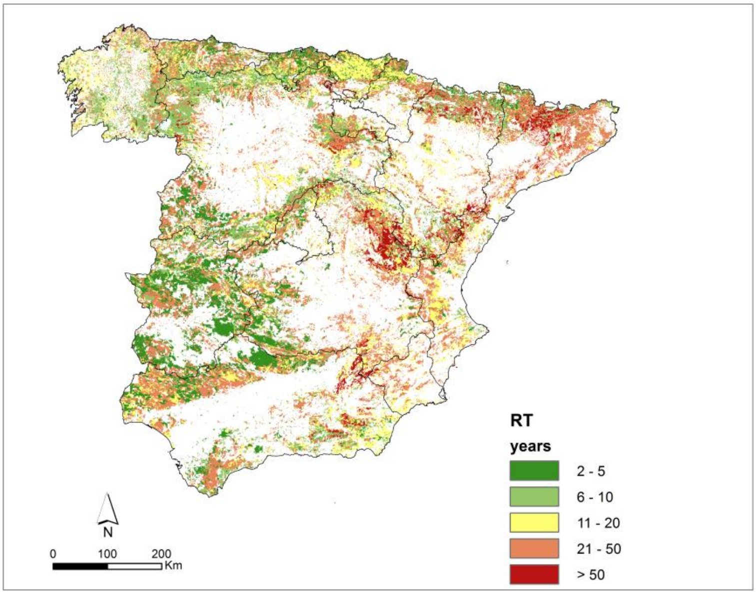


Figure 6. Spatial distribution of the post-fire vegetation recovery time.

Results suggest a RT range from 2 to approximately 100 years for grassland communities and tree communities with low germination (mainly *Pinus nigra* and *Pinus sylvestris*), respectively. However, there were significant differences in the geographical distributions of times, mainly between Euro-Siberian and Mediterranean biogeographical regions. The higher RTs were obtained for low seeding tree communities, located mainly on the Mediterranean coast, ranging from 45 to 100 years. We also found both high seeding and resprouter tree communities, with average RTs around 21 and 25 years, respectively. It should be noted that despite having similar average RT values, there is great difference between the maximum RTs, with values near 40 years in the case of high seeding trees and 50 years for resprouter trees in the Mediterranean region. Shurbland communities showed a RT span around 8 and 13 years in resprouter and seeder communities. Finally, grassland areas presented the lower RT, at an average of 2.5 years.

Regarding the PSGC influence, although they contributed significantly to the recovery time, this contribution was around an average of 22%, exceeding 60% of RT in some areas. The highest values of PSGC contribution were found in the Mediterranean region in areas with low water availability influenced by significant negative winter rainfall trends. This means that the RTOC, which reflects the structure and regeneration of the dominant plants, has the higher contribution to the RT (around 78% of the final RT).

Table 4. Statistical summary of the post-fire recovery time for each vegetation category.

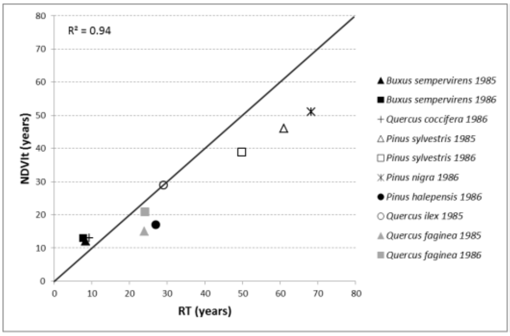
Plant community	Min time	Max time	Avg time	Stdev
Grassland	2	5.3	2.6	0.40
Resprouter shrubland	6	15.8	8.1	1.95
Seeder shrubland	10	26.4	13.5	2.80
Resprouter tree	20	51.1	25.5	4.37
High seeding tree	15	39.6	21.5	4.64
Low seeding tree	45	100.7	52.9	7.62

Table 5. Statistical summary of validation results. The results are characterized in terms of year of burning (Year), number of pixels of RT (N), maximum value of RT (RT Max), minimum value of RT (RT Min), average value of RT (RT Avg), recovery threshold according to the NDVI evolution ($NDVI_t$), pre-fire NDVI value (NDVI 84), and accuracy of the projected NDVI evolution curve (R^2 Regr)

Specie	Year	N	RT_{Max}	RT_{Min}	RT_{Avg}	$NDVI_t$	$NDVI_{84}$	R^2
Pinus sylvestris	1985	4	53	83	61	46	0.69	0.79
Pinus sylvestris	1986	5	49	51	50	39	0.69	0.82
Pinus nigra	1986	6	50	98	68	51	0.67	0.72
Pinus halepensis	1986	4	26	29	27	21	0.62	-
Quercus ilex	1985	1	29	29	29	29	0.60	0.70
Quercus faginea	1985	5	21	29	24	15	0.61	0.71
Quercus faginea	1986	4	22	26	24	21	0.68	-
Quercus coccifera	1986	6	7	13	9	13	0.68	-
Buxus sempervirens	1985	2	7	10	8	12	0.57	-
Buxus sempervirens	1986	1	6	10	8	13	0.59	-

5.2. Model validation

According to the validation results (Figure 7 and Table 5), the observed NDVI recovery span is reasonably similar (R^2 = 0.94) to the RT prediction, although shorter. The overall observed behavior is an overestimation of the RT in tree communities whereas in shrubland communities RT seems to be underestimated. The best performance is achieved in resprouter shrubland (*Quercus coccifera* and *Buxus sempervirens*), and resprouter tree (*Quercus ilex* and *Quercus faginea*) communities, with differences between RTs and NDVI under 5 years. Seeding tree communities, both high and low seeding (*Pinus halepensis*, *Pinus sylvestris* and *Pinus nigra*), showed the poorest agreement with differences of 6 years in high seeding tree communities and more than 15 years in low seeding trees (*Pinus nigra*).



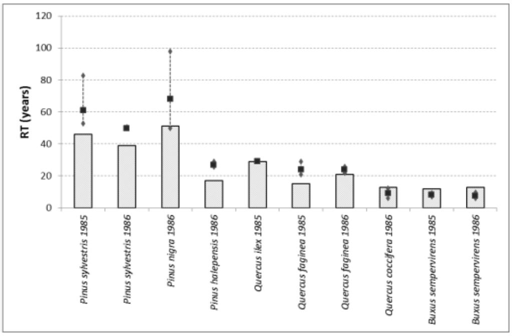


Figure 7. Validation results in burned plots. Scatterplot RT-NDVIt (left). RT range (dotted line), average RT (black square), and NDVI recovery time values (filled bars) (right).

6. Discussion

Some plant species are better adapted to fire than others, depending on the regeneration strategies and horizontal and vertical continuity (Baeza and Roy, 2008). Particularly, plant communities in the Euro-Siberian region present lower RT values due to both the presence of resprouter communities, considered as highly resilient (Rodrigo *et al*., 2005), and the higher water availability due to Atlantic climate conditions. On the other hand, in the Mediterranean region, predominantly on the Mediterranean coast, higher RTs were reported. This occurs as a consequence of, among other factors (ecological, edaphic, topographic, land use, etc.), low water availability due to low rainfall, as well as to the frequent torrential rainfall events in autumn (Baeza *et al*., 2007; Bisson *et al*., 2008) thus increasing soil loss. Rainfall during the first autumn after a fire is particularly crucial for the germination of most seeders (Moreno and Oechel, 1992) since dry conditions likely delays post-fire regeneration in seeding communities (Rodrigo *et al*., 2004). However, the site-level soil water availability is the result of the interaction of precipitation inputs with various factors such as soil depth, type and degradation, and topography. Besides, the temporal distribution of rainfall and factors such as the history of disturbances also influences the recovery time. In any case, it seems that the type and characteristics of the vegetation are the most important parameters influencing the post-fire regeneration process (Alloza *et al*., 2006; de la Riva *et al*., 2008). Accordingly, the post-fire vegetation dynamics seem to differ substantially between the studied seeding and resprouting communities as the latter are highly fire-resilient with a much faster vegetation recovery rate (Brocano *et al*., 2005; Duguy *et al*., 2012; Pérez-Cabello and Ibarra, 2004). However, differences in RT are not restricted to average values. Resprouter communities, mostly resprouter tree communites, show less variability in the RT values than the seeding ones according to the standard deviation values reported in Table 4 (4.37 in resprouter tree communities, 4.64 in high seeding tree, and 7.62 in low seeding tree). This might occur because in ecosystems characterised by highly resilient plant communities (resprouter Mediterranean species), site-level abiotic limitations are often overcome by the resprouter's ability to quickly recolognize the open space created by fire with its undamaged below-ground organs (Duguy *et al*., 2012).

On the other hand, the results from the validation procedure, have confirmed that the overall performance of the proposed methodology (R^2=0.94) is sufficient to consider the method a useful tool for supporting regional forest management and planning. According to the validation results, the best performance is observed in resprouter shrubland (*Quercus coccifera* and *Buxus sempervirens*), and resprouter tree (*Quercus ilex* and *Quercus faginea*) communities, whereas seeding tree communities (*Pinus halepensis*, *Pinus sylvestris* and *Pinus nigra*) showed the poorest agreement. In tree communities, RT values appear to be overestimated, compared to the NDVI recovery time span. This is most likely related to the fact that a similar spectral response of the plant does not always implicate a complete physiognomic recovery, mainly because the NDVI is more related to vegetation cover (Tanase *et al*., 2011). In addition, it should be noted that in some cases (*Pinus halepensis* for instance) the NDVI evolution could be strongly influenced by the presence of other associated plant communities, such as shrublands or grasslands (Pérez-Cabello, 2002; Pérez-Cabello and Ibarra, 2004).

Despite the promising overall results, the validation sample should be increased to cover the high variety of plant communities in the mainland Spain. Consequently, the results reported for the validation should be considered as a pilot validation that mainly aims to exemplify the procedure. Developing a validation sample sufficiently wide to be used for full validation would be very time consuming, involving the characterization of numerous burned plots, and gathering and correcting a great amount of remote sensing images. Nevertheless, RT values obtained for the different communities analyzed are reasonably similar to the expected periods in accordance with the existing literature. In the case of resprouter communities Rodrigo *et al*. (2005) indicate that they reach similar pre-fire cover about 30 years after the fire, a time span close to the average 25.5 years obtained following the method proposed in this work (RT values are showed in table 4). Brocano *et al*. (2005) and Perez-Cabello and Ibarra (2004) indicated similar recovery time intervals. In high seeding tree communities (*Pinus halepensis*) Brocano *et al*. (2005), Kazanis and Arianoutsou (2004), Ruano *et al*. (2012), and Trabaud (1998) suggest recovery times starting from 15 years, reasonably similar to the 21.5 years obtained in this study. Finally, the high RT values calculated in the case of low seeding tree (*Pinus nigra* and *Pinus sylverstris*) are consistent with

Rodrigo *et al*. (2004) who indicated that there is little chance of recovery of the original pre-fire situation which supports the existence of a very long RT. However, it should be noted that RT values are not equally reliable since the validation sample does not cover the whole RT range. Accordingly, the most reliable recovery times are the values below 21 years, since this is the time period for which NDVI recovery is directly measured in the calibration data. The next most reliable period extends to 51 years, the time period for which NDVI recovery has been indirectly measured. Beyond 51 years is the least reliable period which should be carefully considerate.

We can conclude that the recovery time calculated from the RT method is reasonably similar to the recovery threshold obtained from the NDVI evolution, particularly in resprouter communities. However, there is a certain degree of uncertainty insofar as we are providing a regional scale assessment. This uncertainty is mainly linked to the quality of the input data and to the capacity of the NDVI for monitoring vegetation recovery. The first source of uncertainty, quality of the input data, is inherent to the geographical information, since it is not possible to find a data source that perfectly represents real conditions, especially when working at regional scales. For instance, errors in the spatial distribution of plant communities in the Spanish Forestry Map are influencing the whole RT calculation process because all the assumptions are made on its basis. On the other hand, the uncertainty related to the NDVI as a tool for monitoring post-fire vegetation recovery comes from the fact that the NDVI takes into account the vegetation cover rather than the physiognomy of the plants, which can lead to misinterpretation of the observed recovery time span. However, the comprehension of its limitations allows the use of the NDVI as a reference for validation purposes. Furthermore, note that the proposed method for RT assessment also has some limitations and drawbacks, although it may be considered as a relative improvement compared to similar methods designed to evaluate post-fire dynamic processes like Duguy *et al*. (2012) or Bisson *et al*. (2008), since our methodology offers a framework for its implementation at regional scale as well as quantitative results. The main drawback arises from the fact that, although we conducted an extensive literature review to support our choices, there is still some subjectivity in the values of RTOC or PSGC increase ratios. This fact is particularly important when applying the method to a different region, as it is very likely that either plant species and/or environmental conditions differ significantly from those described herein. So, a deep comprehension of the mechanisms and factors that lead the post-fire dynamics is necessary to properly apply the method to a different area. Nonetheless, it is difficult to establish a direct comparison of our work and the one developed by Duguy *et al*. (2012) or Bisson *et al*. (2008) mainly because both outputs and analysis scale are different.

7. Conclusions

This paper presents a methodological approach for assessment on a regional scale of the recovery time of plant communities after high severity wildfires. The method is based on map algebra calculations and a few representative variables, which could ensure the applicability of the method to other study areas. In addition, a validation procedure based on multi-temporal monitoring of the evolution of the NDVI is also described and exemplified in a pilot area (Huesca Pyrenees).

Our results indicate a high heterogeneity in RT values, both between the examined plant communities and the various regions of peninsular Spain. This is not surprising, given that peninsular Spain has a wide range of physical and environmental conditions. This is mainly due to the coexistence of two contrasting biogeographic regions (Euro-Siberian and Mediterranean), which also show a high internal variability in conditions, directly linked to variability in terrain and the resulting different climatic conditions. This fact increases the complexity of the analysis of any environmental parameter or process, especially at regional scales.

The PSGC contributed significantly to the reconstruction time, however, type and characteristics (structure and regeneration strategy) of the dominant plant community seem to be the most important parameter influencing the post-fire regeneration process.

On the other hand, although the validation results are restricted to ten fire events that occurred in 1985 and 1986, and extending the validation to the whole peninsular Spain will be a very time-consuming process, involving the gathering and correction of a great amount of remote sensing images; in general lines we consider that the RT values obtained are reasonably well adjusted to the expected evolution of plant communities after fire disturbance.

In any case, we believe that the proposed method is sufficiently strong to be valuable in several fields, such as land management, forest fires, assessment of socioeconomic vulnerability, and environmental services. This applicability is mainly due to the simplicity of the method, which requires few variables. Additionally, the methodology is integrated and developed within a GIS that allows one not only to map the results but also to perform different kinds of spatial analyses and mapping. Additionally, we are working on extending the validation procedure in the framework of another project focusing on the development of predictive models of ecological vulnerability to fire.

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CHAPTER 9. CONCLUSIONS AND FURTHER WORK

This chapter summarizes the main conclusions of this PhD thesis as well as introduces some of the possible future developments of an ongoing research.

9.1. Main conclusions

Exploring new methods for wildfire modeling requires taking into account several dimensions of the wildfire phenomena. Forest fires hazard significantly varies in space and time. Therefore components have to be adequately considered regardless the model or method used. In addition, addressing the potential uncertainty arising from either data or methods is also mandatory since it allows establishing the limitations of the results as well as informs about its reliability and usefulness.

The methodologies proposed in this work have all been developed and employed considering these dimensions. All methods are spatial explicit methods that reflect in greater or lesser extent the spatial variability of forest fires and their potential impacts. In this regard, although overall every method deals with the spatial dimension, two statistical methods stand above the rest due to its ability for modeling the space component.

- On the one hand, GWR, being a technique specifically devoted to include the spatial component into regression procedures, allows capturing not only the spatial variability of wildfire driving factors but also determine and quantify their contribution and errors.
- On the other hand, RF algorithms have proved to be a useful tool, overcoming traditional regression and other ML methods both in terms of improving their prediction accuracy and capturing the spatial variability of wildfires.

The temporal dimension of fires has also been deeply explored. Temporal trends have been identified both in number of fires and burnt area size, confirming that fire is neither a temporal stationary hazard and granting to detect areas where wildfires are increasing and with higher danger. Furthermore, the fit of statistical models of wildfire occurrence provides insights into the temporal variability of forest fires. This behavior is analyzed from historical fire occurrence and synthetized into prospective models which aim to foresee –in a probabilistic way– the most likely evolution of human-caused wildfires. This temporal dimension is even more evident when talking about the methodology developed for quantitative analysis of ecological vulnerability whose outputs are expressed in temporal terms (recovery time) and includes climate trends as one of its main calculation parameters.

A certain degree of uncertainty is always present when dealing with environmental processes, a fact that is also inherent to statistical models. In this regard, uncertainty has been addressed in all the works that integrate this thesis. Overall, all methods are validated in one way or another, whether we refer to predictive accuracy, comparison with previous works or exploring and comparing similar methods or procedures. However, the major shortcoming detected while developing most of the proposed methods is the quality of the input data, particularly occurrence data. This issue is affecting all the analysis devoted to explore new methods for modeling anthropogenic causality in forest fires (GWR and ML) since ignition location and cause is the main input and consequently influences model outputs. The spatial distribution of wildfire occurrence greatly varies from one region to another depending on the assumptions made when considering the ignition cause and source, leading to different predictions. This is mainly due to the lack of homogeneous criteria in fire event recording and classification.

Developing and exploring the applicability new methods entails the use of appropriate tools for its proper implementation. In this sense, this thesis has deeply explored the use of several tools, combining conventional GIS approaches with statistical and programming languages, either open source or proprietary. *Scripting* languages either applied to GIS analyses or statistical methods are essential tools when implementing some of the proposed methods since they allow designing complex analysis workflows over big data.

Specific findings

Following the specific findings according to the sub-objectives presented in chapter 2 are summarized.

i. Provide insights into the temporal evolution of wildfires:

- Forest fire events have significantly increased in the EUMed Region during the last 25 years, whereas the annual burned area presents a reverse behavior, with a generalized decrease in the period 1980-2009. Particularly, Portugal, Spain and the area of Sicilia in the south of Italy, appear as the regions with the highest fire impact, since they present both increasing number of fires and burned areas. However, there is a significant spatial variation in the detected trends.

iii. Explore the applicability of new regression methods for modeling of human causality:

- ML models improve the prediction accuracy of traditional regression methods. Either RF or BRT models yield an improvement in accuracy over LR methods for wildfire occurrence assessment, according to AUC values.
- RF seems to be the best choice due not only to its higher accuracy, but also to the fact that fewer predictive variables are required to achieve

this accuracy. In addition, its calibration is easier because it involves few parameters.

- Regardless of the method considered, density of agricultural machinery (DAM) and change in demographic potential (CDP) have proved to be the variables most closely related to fire occurrence, although this result is partially due to the continuous nature of these variables and, in the case of DAM, to interaction with other predictive variables like wildland-agricultural interface (WAI). In any case, fire occurrence in Spain is mainly related to the increase of human pressure on wildlands and to accidents or negligence in the course of agricultural work.

iv. Estimate the spatial variation of the explanatory factors of human causality:

- The use of GWR techniques applied to logistic regression (LR) models has corroborated the existence of spatial variation in the explanatory factors associated with human causality in wildfires.
- GWR improves the predictive performance of LR by considering regression as a non-stationary process. However, GWR techniques are quite computational demanding and time consuming.

v. Analyze the reliability of the original data of fire occurrence and potential associated uncertainty:

- The lack of homogeneous criteria among the autonomous regions on forest fire management is a potential source of uncertainty for wildfire risk assessment which is affecting both the predicted probability values as well as the spatial pattern of probability.
- The spatial distribution of wildfire ignition greatly varies depending on the assumptions made when selecting the ignition cause and source, leading to different predictions. However, it is possible to determine the best scenarios for modeling wildfire occurrence or risk. According with our results the best choice is consider both known and supposed causes with a proportion of forest fires with unknown source.
- Uncertainty is also affecting the contribution of the explanatory variables. Results suggest that DAM, CDP, WAI and protected areas (PA) are the least sensitive variables to variations in the spatial distribution of the occurrence.

vi. Estimate the ecological vulnerability of plant communities affected by fire:

- There is high heterogeneity in recovery time values, both between the examined plant communities and the various regions of peninsular Spain due to the coexistence of two contrasting biogeographic regions (Euro-Siberian and Mediterranean), which also show a high internal variability in conditions, directly linked to variability in terrain and the resulting different climatic conditions.
- Plant species growth constraints (PSGC) contributed significantly to the reconstruction time, however, type and characteristics (structure and regeneration strategy) of the dominant plant community seem to be the most important parameter influencing the post-fire regeneration process.

9.2. Future development proposals

Although this work provides deep insights into the application of relatively new approaches for wildfire modeling, evidently there are still several ways to improve it, which may lead to further research. Overall the spatial dimension of wildfire occurrence modeling has been addressed in detail. Nevertheless, it would be appropriate explore new possibilities for spatializing both dependent and explicative variables, leading to multi-scale developments or enhancing the spatial accuracy of the models.

The research field that, in my opinion, is more promising for future developments is the analysis of the temporal dimension of forest fires models. Specifically, dynamic models –in the sense of varying over time- should be explored to produce daily estimations of human-caused fires. In the same way, assessing the temporal evolution of the driving factor of human causality may be an interesting research subject. Following, several specific proposals for further research are presented:

i. New predictors as well as new methods for spatialization (distance to interfaces, density maps and so on) could be explored and tested.

ii. The temporal dimension in fire risk could be included in aiming to develop dynamic models.

iii. The calibration of SVM methods should be explored more in depth in order to properly address its predictive performance.

iv. The use of different probability distributions such as Poisson combined with the GWR approach could provide new insights into human-caused wildfire modeling.

v. Combining ensemble model methods and local regression methods (boosting moving window regression) might improve its standalone versions.

vi. Change scenarios (land cover/climate change) should be considered for future developments of ecological vulnerability assessments.

9.1. Conclusiones principales

Explorar nuevos métodos para el modelado de incendios forestales implica la consideración de sus diferentes dimensiones. El riesgo de incendio varía significativamente espacial y temporalmente. Por lo tanto, estos dos componentes deben ser debidamente considerados con independencia del modelo o método utilizado. Además, hacer frente a la posible incertidumbre derivada de datos o métodos es también es un requerimiento en tanto en cuanto permite establecer las limitaciones de los resultados, así como informar su fiabilidad y utilidad.

Todas las metodologías propuestas en este trabajo han sido desarrolladas tomando en consideración estos dimensiones. Todos los métodos tienen una base espacialmente explicita que refleja en mayor o menor medida la variabilidad espacial de los incendios y sus potenciales impactos. En este sentido, aunque en general todos métodos incluyen la dimensión espacial, dos de ellos destacan dada su particular idoneidad para modelar fenómenos espaciales:

- Por una parte, la GWR, siendo una técnica especialmente diseñada para considerar el componente espacial, permite capturar no sólo la variabilidad espacial de los factores explicativos de los incendios sino también determinar y cuantifica su contribución y error.
- Por otra parte, el algoritmo RF ha probado sobradamente su utilidad, superando tanto a los métodos de regresión tradicionales como a otros métodos ML, tanto en términos de precisión en la predicción como en su capacidad para capturar la variabilidad espacial de los incendios forestales.

La dimensión temporal de los incendios ha sido también abordada y analizada en profundidad. Se han identificado tendencias temporales tanto en el número de incendios como en la superficie quemada, confirmando que los incendios no son un fenómeno estático, permitiendo además detectar zonas donde la ocurrencia de incendios se ha visto incrementada, aumentando por tanto el peligro asociado. Además, el ajuste de modelos estadísticos de ocurrencia permite profundizar en su variabilidad temporal. Se analiza este comportamiento gracias al estudio de la ocurrencia histórica y se sintetiza en modelos prospectivos con objeto de predecir –en términos probabilísticos– la evolución más probable de los incendios de origen antrópico. Esta dimensión temporal se pone aún más de manifiesto si nos centramos en la metodología desarrollada para el análisis cuantitativo de la vulnerabilidad ecológica, cuyos resultados se expresan en términos de temporales (tiempo de recuperación), incluyendo además tendencias climáticas como uno de los parámetros principales para su cálculo.

Tratar con procesos ambientales siempre conlleva cierto grado de incertidumbre, aspecto que es además inherente al uso de modelos estadísticos. En este sentido, todos los trabajos que componen esta tesis doctoral incluyen la incertidumbre en sus análisis. En general, todos los métodos han sido sometidos a validación de un modo u otro, ya sea al hacer referencia a la capacidad predictiva, a su comparación con otros trabajos o explorando métodos o procedimientos alternativos. Sin embargo, el mayor inconveniente detectado al desarrollar la mayoría de métodos ha sido la calidad de los datos de entrada, concretamente en la información sobre ocurrencia. Este problema afecta a todos y cada uno de los métodos utilizados para modelar la causalidad humana (GWR y ML) en incendios forestales ya que la información referente a la localización y causa de la ignición es su principal fuente de información e influye por lo tanto en los resultados. La distribución espacial de la ocurrencia de incendios varía enormemente entre las diferentes regiones en función de los supuestos hechos al considerar la causa de la fuente ignición, dando lugar a diferentes predicciones. Esto es debido principalmente a la falta de criterios homogéneos en el registro y clasificación de los partes de incendio.

Desarrollar y explorar la aplicación de nuevos métodos supone el uso de herramientas apropiadas para su correcta implementación. En este sentido, la presente tesis ha explorado en profundidad diversas herramientas, combinado aproximaciones SIG convencionales con lenguajes de programación y estadísticos, tanto de código abierto como propietarios. Los lenguajes de *scripting*, ya sean aplicados a análisis SIG como a métodos estadísticos, son herramientas indispensables para implementar algunos de los métodos propuestos ya que permiten diseñar flujos de análisis complejos utilizando grandes conjuntos de datos.

Conclusiones específicas

A continuación se recogen las conclusiones específicas para los sub-objetivos presentados en el capítulo 2:

i. Proporcionar perspectivas sobre la evolución temporal de los incendios forestales:

- El número de incendios forestales en la Europa mediterránea se ha incrementado significativamente durante los últimos 25 años, mientras que el área total quemada presenta un comportamiento opuesto, con un descenso generalizado en el periodo 1980-2009. Concretamente Portugal, España y la zona de Sicilia en el sur de Italia parecen ser las regiones más afectadas ya que presentan un incremento tanto en número de incendios como en área quemada.

iii. Estudiar la aplicabilidad de nuevos métodos de regresión para modelar la causalidad humana:

- Los modelos ML mejoran la precisión en la predicción de los métodos clásicos de regresión. Tanto RF como BRT mejoran los resultados obtenidos utilizando LR según los valores de AUC obtenidos.
- RF se presenta como la mejor elección no solo por su mayor precisión sino porque requiere menos variables explicativas para alcanzar dicha precisión. Además, su calibración es más sencilla al utilizar menos parámetros.
- Con independencia del método seleccionado, la densidad de maquinaria agrícola (DAM) y el cambio en el potencial demográfico (CDP) se conforman como las variables relacionadas más estrechamente con la ocurrencia de incendios, aunque ello está motivado en parte por la naturaleza continua de dichas variables y, en el caso de DAM, con la interacción con otras variables como la interfase agrícola-forestal (WAI). En cualquier caso, la ocurrencia de incendios forestales en España está principalmente relacionada con el incremento de la presión humana sobre zonas forestales y con accidentes o negligencias derivados de la actividad agrícola.

iv. Estimar la variabilidad espacial de los factores explicativos de la causalidad humana:

- El uso de técnicas GWR aplicadas a modelos de regresión logística (LR) ha corroborado la existencia de variación espacial en los factores asociados con la causalidad humana en incendios forestales.
- GWR mejora la capacidad predictiva de LR al considerar la regresión como un proceso no estacionario. Sin embargo, las técnicas GWR son computacionalmente exigentes y requieren largo tiempo de ejecución.

v. Analizar la fiabilidad de los datos originales de ocurrencia de incendios y su potencial incertidumbre asociada:

- La inexistencia de un criterio homogéneo entre las CCAA en materia de gestión de incendios forestales es una fuente potencial de incertidumbre para la estimación del riesgo de incendio, que afecta tanto a las predicciones realizadas como a sus patrones espaciales.
- La distribución espacial de la ignición depende en gran medida de las asunciones realizadas al seleccionar el origen y causa de la ignición, lo que conduce a predicciones diferentes; sin embargo, es posible determinar cuál es el mejor escenario para modelar la ocurrencia de

incendios. De acuerdo con esto, los resultados sugieren que la mejor elección es considerar incendios con causa conocida y supuesta, incluyendo una proporción de aquellos incendios con causa desconocida.

- La incertidumbre afecta también a la carga explicativa de las variables explicativas. Los resultados sugieren que DAM, CDP, WAI y espacios protegidos (PA) son las variables menos sensibles a la variación espacial de la ocurrencia.

vi. Estimar la vulnerabilidad ecológica de las comunidades vegetales afectadas por el fuego:

- Existe una elevada heterogeneidad en los valores de tiempo de recuperación tanto entre las comunidades vegetales analizadas como entre las diferentes regiones de la España peninsular debido a la coexistencia de dos regiones biográficas con condiciones ambientales muy contrastadas (Eurosiberiana y Mediterránea), que a su vez presentan una importante variación interna es su condiciones, debido a la variabilidad y complejidad del relieve, lo que conduce a condiciones climáticas distintas.
- Los factores limitantes del desarrollo de las especies vegetales (PSGC) tienen una contribución significativa en el tiempo de reconstrucción; sin embargo, el parámetro determinante en la regeneración post-fuego parece ser el tipo y características (estructura y estrategia reproductiva) de las comunidades vegetales dominantes.

9.2. Líneas de trabajo futuras

Aunque este trabajo profundiza en la aplicación de aproximaciones relativamente novedosas para el modelado de incendios forestales, evidentemente existen algunas posibles líneas de mejora a considerar en futuros desarrollos. En líneas generales, la dimensión espacial en el modelado de la ocurrencia se ha estudiado detalladamente, pero, en cualquier caso, sería apropiado explorar nuevas posibilidades en la espacialización de las variables dependientes y explicativas, de cara a desarrollos multi-escala o con mayor precisión espacial en los modelos.

El ámbito de investigación que, en mi opinión, es más prometedor para desarrollos futuros es el análisis de la dimensión temporal en el modelado de incendios forestales. Específicamente, se deberían explorar modelos dinámicos –en el sentido de variabilidad temporal– para desarrollar estimaciones diarias en la causalidad humana. De un modo similar, analizar la evolución temporal de los factores causales podría ser otra interesante línea de trabajo. A continuación se presentan diferentes propuestas de futuros desarrollos de la investigación:

i. Podrían considerarse nuevos factores predictivos, así como nuevos métodos de espacialización (distancia a las interfaces, mapas de densidad, etc.).

ii. La dimensión temporal en el riesgo de incendio podría ser incluida con objeto de desarrollar modelos dinámicos.

iii. La calibración de los métodos SVM debería ser estudiada con mayor detalle para estimar adecuadamente su capacidad predictiva.

iv. Explorar la aplicación de otras distribuciones de probabilidad aplicadas sobre GWR podría conducir a nuevas aproximaciones en el modelado de incendios con causa humana.

v. Combinar métodos de ensamblado (*bagging* or *boosting*) con métodos locales de regresión (*boosting moving window regression*) podría mejorar su aplicación por separado.

vi. El análisis de escenarios de cambio –cobertura del suelo, cambio climático– debería incluirse en futuras versiones de estimación de vulnerabilidad ecológica.

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APPENDIX A. INTEGRATING GEOSPATIAL INFORMATION INTO FIRE RISK ASSESSMENT

This appendix introduces the work "Integrating geospatial information into fire risk assessment" which summarizes the main outputs from project FIREGLOBE as well as contextualizes the framework of research.

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Integrating geospatial information into fire risk assessment

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Abstract. Fire risk assessment should take into account the most relevant components associated to fire occurrence. To estimate when and where the fire will produce undesired effects, we need to model both (*a*) fire ignition and propagation potential and (*b*) fire vulnerability. Following these ideas, a comprehensive fire risk assessment system is proposed in this paper, which makes extensive use of geographic information technologies to offer a spatially explicit evaluation of fire risk conditions. The paper first describes the conceptual model, then the methods to generate the different input variables, the approaches to merge those variables into synthetic risk indices and finally the validation of the outputs. The model has been applied at a national level for the whole Spanish Iberian territory at 1-km^2 spatial resolution. Fire danger included human factors, lightning probability, fuel moisture content of both dead and live fuels and propagation potential. Fire vulnerability was assessed by analysing values-at-risk and landscape resilience. Each input variable included a particular accuracy assessment, whereas the synthetic indices were validated using the most recent fire statistics available. Significant relations ($P < 0.001$) with fire occurrence were found for the main synthetic danger indices, particularly for those associated to fuel moisture content conditions.

Additional keywords: fire propagation, fuel moisture content, geographic information systems, human factors, remote sensing, vulnerability.

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Introduction

Biomass burning is widely recognised as one of the critical factors affecting vegetation succession and carbon budgets worldwide (Chuvieco 2008; Thonicke *et al.* 2010). At a global scale, the effects of fire on the atmospheric chemistry are very significant as recent studies estimate that the amount of CO_2 released by biomass burning is approximately half (3–4 Pg C) of that released by fossil fuels consumption (Bowman *et al.* 2009; van der Werf *et al.* 2010). At regional and local scale, fires also have important socioeconomic implications, affecting both lives and structures (Chuvieco *et al.* 2010).

Fire is very influential in vegetation succession and distribution. It is a natural factor, as it may be caused by lightning or volcanic eruptions, but since humans have been able to produce fire for their own means, they have extended the influence of fire beyond its ecological limits, transforming ecosystems worldwide (Bond *et al.* 2005). Fire has offered human beings a powerful tool not only for their warming and cooking, but also for protection, hunting, land clearing and soil fertilisation (Bowman *et al.* 2011). However, fires can also have catastrophic effects on human lives and resources, particularly when severe fire seasons arise, as was the case recently in Greece (2007), Australia (2009) and Russia (2010), where overall more than 300 people were killed and 7000 houses destroyed.

Within this context, the value of having better tools for fire prevention and assessment should be emphasised. Fire risk evaluation is a critical part of fire prevention, because pre-fire resources planning requires the use of objective tools to monitor when and where a fire is more likely to occur, or when and where it will have more negative effects. A wide variety of fire risk assessment studies have been published in the last few years (Sebastián-López *et al.* 2002; Allgöwer *et al.* 2003; Riera and Mogas 2004; Kaloudis *et al.* 2005; Amatulli *et al.* 2006; Stratton 2006; Cooke *et al.* 2007; Prasad *et al.* 2008; Beverly *et al.* 2009; Loboda 2009; Padilla and Vega-García 2011). They include different spatial scales and variables, and diverse risk schemes. Using a standardised approach would help risk evaluation efforts, facilitating the integration of data and the generation of regional and global assessments (Thompson and Calkin 2011).

Concepts involved in fire prevention

The conceptual definition of a fire risk assessment system should include the most relevant components associated with the fire process. Terminology used in fire prevention planning has a long tradition, especially in the US and Canada, but is still quite controversial, especially when comparing its terms with those used in other natural hazards (earthquakes, volcanic eruptions, floods, etc.). Following the most common terminology used by fire managers, 'fire hazard' refers to the potential fire behaviour associated with the 'static' properties of fuel, regardless of the particular moisture conditions on a given day. The term 'fire risk' refers to the 'chance of fire starting, as determined by the presence and activity of causative agents' (mainly lightning and human factors). The concept of 'fire danger' is broader and describes the 'factors affecting the inception, spread and resistance to control, and subsequent fire damage; often expressed as an index' (NWCG 2003). Following this approach, fire danger includes various factors: weather conditions, causative agents and even potential damage, but most commonly the latter are not considered in operational fire danger assessment systems (San Miguel-Ayanz *et al.* 2003). Some authors are critical of the term 'danger', as its meaning is vague, and suggest fire hazard or fire probability be used instead (Bachmann and Allgöwer 2001).

In other natural hazards, the term 'risk' commonly describes the convergence of the physical probability that a natural event occurs, and its potential damage to people and the environment (UNISDR 2009). Following this approach, fire risk mapping should include the assessment of values potentially affected by fire. In fact, those values are critical to guide fire suppression efforts (a clear example is when fire occurs in the proximity of urbanised areas). Therefore, the consideration of fire vulnerability (potential effects of fire on social and ecological values) should always be part of fire risk evaluations and would help to align them with other natural hazard assessments.

Several authors have tried to adapt this risk approach to wildland fires (Bachmann and Allgöwer 2001; Allgöwer *et al.* 2003; Chuvieco *et al.* 2003), which implies that fire risk assessment should both include the probability that a wildfire ignites or propagates (which we will name as fire danger throughout this paper), and the expected damages caused by fire behaviour (termed as fire vulnerability). Recent papers on fire risk assessment have incorporated this double evaluation to propose a comprehensive analysis of fire risk conditions (Calkin *et al.* 2010; Chuvieco *et al.* 2010; Tutsch *et al.* 2010; Thompson *et al.* 2011), but still much more research exists on fire danger than on fire vulnerability.

This paper focuses on developing a method for assessing fire risk conditions using a conceptual scheme that may be applicable at different spatial scales. The paper summarises the procedures to generate all required input variables in a spatially consistent way, as geographical data layers. Finally, the paper addresses the integration of the different input variables into synthetic fire risk indices. This risk assessment system was developed within the scope of a Spanish research project (www.fireglobe.es, accessed March 2012) and includes both fire danger and fire vulnerability (Fig. 1). It builds upon a previous fire risk scheme proposed by Chuvieco *et al.* (2010) but greatly extends the consideration of the vulnerability components by integrating fire danger and fire vulnerability. Estimation of danger includes the consideration of fuel characteristics, human and natural causes, wind speed, wind direction and slope gradient. Determination of vulnerability includes the estimation of housing prices in the wildland–urban interface (WUI), as well as some ecosystem services and landscape values that may be affected by fire. Because fire damage lasts until pre-fire conditions are restored, our vulnerability assessment includes an estimation of recovery time after fire, based on vegetation and climate–soil properties, as well as fire behaviour scenarios. Extensive use of geographic information technologies (GIT) was made for this project, as all the input variables and the final indices are spatially explicit. This paper presents results of the fire risk index developed at a national scale, with a spatial resolution of 1 km^2, covering the Peninsular territory of Spain (490 000 km^2).

Methods

The development of an operational fire risk assessment system requires three steps: generation of required input variables, proposal of ways to integrate them into synthetic indices and dissemination of indices to forest managers. These three steps require different methodologies, which are summarised in the next sections and in Table 1. Fire risk indices have many potential uses, the main one being to reduce the negative effects of fire by introducing risk reduction strategies.

Generation of input variables for fire danger

A wide variety of studies has been published in recent decades on methods to generate relevant data for fire risk assessment. To

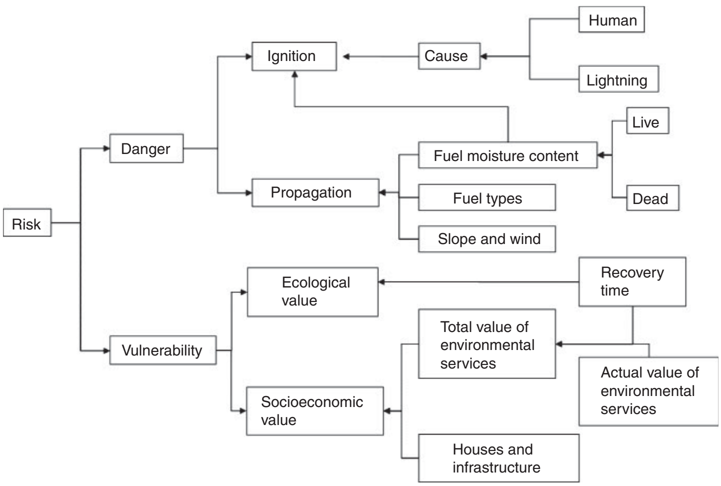

Fig. 1. Proposed framework for an integrated fire risk assessment system (adapted from (Chuvieco *et al.* 2010).

Table 1. Sources for the main inputs of the fire risk assessment system

Factor	Methods	Input variables
Human factor	Spatial modelling statistical approach, logistic geographically weighted regression	Historical fire records (1988–2007); wildland–agricultural interface; wildland–urban interface; natural protected areas; power lines; tracks in forest areas; railroads; density of agricultural machinery
Lightning	Statistical approach	Meteorological data, lightning strikes, forest maps
Live FMC	Field work simulation models	Satellite images
Dead FMC	Field work statistical approach	Meteorological data
Propagation	Modelling techniques	Spanish fuel type map, Spanish forest map, canopy cover product, digital terrain models, meteorological data
Socioeconomic vulnerability	Economic analysis sample studies	Wood and non-wood products statistics, forestry inventory and maps, hunting fishing and recreational use of forests statistics, pastureland prices, CO_2 stock estimations, carbon prices, housing prices
Ecological vulnerability	Field work, ecological and erosion models	Soil, vegetation and land use maps, protected areas, satellite images, digital terrain data, ecoregions, climatic maps

explain them in detail would exceed the scope and appropriate length of this paper. We will briefly review them in the context of the choices made in the current study. All these methods heavily rely on spatial information and therefore the sources of input data are closely linked to GIT; mainly satellite remote sensing and GIS. All variables were mapped at the target resolution of 1 km^2 and georeferenced in the UTM standard projection system (extended zone 30, using the WGS84 ellipsoid).

The influence of human factors on fires can be considered as both a cause and an effect. Studies pertaining to the former aspect are more abundant, because human activities are the most common cause of fires (95% of Spanish fires are human-caused according to national statistics, Martínez *et al.* 2009). Identifying the most important factors involved in fire occurrence has been the main goal of a wide range of studies, commonly based on statistical approaches, which try to explain historical human-caused fire occurrence based on a set of independent variables (Syphard *et al.* 2007; Archibald *et al.* 2009; Martínez *et al.* 2009; Chuvieco and Justice 2010; Padilla and Vega-García 2011). The consideration of human values in fire risk assessment is more recent and only a few regional studies have identified that the main socioeconomic damages potentially caused by wildland fires are associated with lives, property and environmental services (wood products, hunting, fungi, carbon stocks, recreational, etc.) (Loomis 2004; Venn and Calkin 2009).

Previous studies in several Spanish regions (Chuvieco *et al.* 2010) demonstrated the importance of taking into account regional variation in human factors when explaining fire occurrence. This spatial diversity may be approached either by creating different models for specific types of region (more-or-less urbanised, for instance) or using spatially explicit statistical tools. We have chosen the latter approach by using geographically weighted regression analysis (GWR) (Fotheringham *et al.* 2002) to model human patterns of fire occurrence in the study area. We used the logistic regression model of GWR (LGWR), as logistic regressions have been previously used to model human-caused fires (Martínez *et al.* 2009; Preisler *et al.* 2011). Modelling with LGWR methods required us to first generate spatial distributions of both dependent (high or low fire occurrence, defined by a threshold of fires km^{-2}) and independent (explanatory) variables at 1-km^2 resolution. Fire occurrence was computed from national fire statistics for the 1988–2007 period, selecting those fires larger than 1 ha. The LGWR model was built with 60% of the sample for calibration and the remaining 40% for validation. The calibration was based on adaptive kernels to obtain the optimised bandwidth through cross validation (Fotheringham *et al.* 2002). To determine the variables that would eventually be included in the final model, an initial LGWR model including all the considered variables was established, discarding in the final model those variables that either were not significant ($P > 0.05$), or whose explanatory sense was not consistent with what would be expected based on prior experience and expert opinion. The validation was based on local determination coefficients (R^2) obtained during the calibration of the model. The local R^2 values provided a first assessment of the degree of fit of the LGWR model. The overall percentage of successfully classified points and the degree of agreement according to the value of Cohen's kappa (Congalton and Green 1999) were also calculated using the validation sample.

Even though fires caused by lightning are less frequent they cannot be underestimated, particularly in some regions of the world with low populated areas (i.e. where human-caused fires are less likely, e.g. >30% of fires in the boreal forest are caused by lightning strikes) (Stocks *et al.* 2003; Krawchuk *et al.* 2009). To include this variable in fire risk models, a good knowledge of spatial distribution of lightning strikes is required, as well as an understanding of why a strike becomes an ignition point (Renkin and Despain 1992; Dissing and Verbyla 2003; Larjavaara *et al.* 2005). As with the human component, our approach to estimating the probability of naturally caused fires was based on empirical methods. Historical patterns of lightning ignitions were related to potential explanatory factors such as the type of lightning strike (whether or not it was associated with rainfall, its polarity, etc.), the slope and elevation, the climate of the affected area, the type of fuel receiving the strike and its moisture content. Logistic regression analysis was used to calibrate models. Climate type, dead fuel moisture content and lightning strikes were found to be the most significant variables in the model (Pacheco *et al.* 2009).

Fuel moisture content (FMC, commonly expressed as percentage of dry weight) is a critical variable for fire ignition and propagation, as it regulates the ignition delay and the amount of energy available for combustion. Consequently, all fire risk assessment systems include, in one way or another, this component. Most commonly, the estimation of FMC is based on weather temporal trends, combined through moisture codes. The best known are those that try to estimate FMC of dead fuels (the materials lying on the forest floor), which are drier and more prone to ignite. The Canadian Fire Weather Index (FWI) and the US National Fire Danger Rating System (NFDRS) estimate FMC of dead fuels using a combination of temperature, relative humidity, rainfall and wind, and compute different indices depending on fuel particle size (Viney 1991; Camia *et al.* 2003). The spatial estimation of these indices is commonly based on interpolation techniques or on gridded, forecasted data. For this project, we have relied on empirical fittings based on field work and meteorological data, which show a good prediction accuracy (RMSE <4% of FMC) for the 10-h code of the NFDRS (Aguado *et al.* 2007). The functions were calibrated and validated for central Spain and then applied to the whole country, based on daily forecasted data (forecasts were available at 0600 hours and they predicted the situation at 1200 hours).

The FMC of live species is not commonly included in fire risk assessment, as it is more difficult to estimate from meteorological data than is dead fuels moisture. Live plants have their own mechanisms to adapt to water shortage so the same meteorological conditions may affect different species in a very different way. Although some studies have tried to estimate live FMC from meteo codes (Viegas *et al.* 2001; Castro *et al.* 2003) the most reliable approach nowadays relies on satellite images. As fuel dries, reflectance increases in the water absorption bands (between 1200 and 2400 nm) and temperature increases as a result of reduced evapotranspiration. Both effects are evident from satellite observation (Ceccato *et al.* 2003). Additionally, many plants reduce chlorophyll activity when drying, which is also observable in the red and near infrared bands (Paltridge and Barber 1988). Estimations of live FMC from satellite data have used both empirical and simulation methods (Zarco-Tejada *et al.* 2003; García *et al.* 2008; Yebra and Chuvieco 2009). We generated live FMC maps from the inversion of simulation models, as this approach provided accurate results in previous projects dealing with Mediterranean grasslands and shrublands (Yebra and Chuvieco 2009). We have extended this approach to Mediterranean woodlands, as well as to grasslands, shrublands and woodlands of the more humid Eurosiberian ecosystems of Northern Spain. Rainfall in the Spanish Mediterranean regions ranges from 400 to 500 mm and reaches 2000 mm in the northern part of the country. In both climate units, the input data were from the MCD43A4 product (http://modis-land.gsfc.nasa.gov/brdf.html, accessed March 2012), obtained from Terra-Aqua MODIS images received by the MODIS reception antenna installed at University of Oviedo (http://www.indurot.uniovi.es, accessed March 2012). This product is computed every 8 days from 16 daily images, has 500-m spatial resolution and includes the correction of the off-nadir observations (Schaaf *et al.* 2002). The estimation of FMC relied on comparing the actual reflectances from the MCD43A4 product to the reflectances simulated using the Prospect, Sailh and Geosail radiative transfer models (Jacquemoud *et al.* 2009). Parameters for these models were derived from field work and laboratory measurements, including the main species of both Mediterranean and Eurosiberian Spanish territory (Jurdao *et al.* 2012). Two different simulations were performed for these two regions considering the ecological conditions of the region in order to avoid unrealistic simulations that may introduce external noise (Yebra and Chuvieco

2009). Estimation errors were assessed by comparing results with FMC measurements taken during fieldwork undertaken in both ecoregions.

Fire propagation modelling is a rather complex topic that has been extensively covered in the forest fire literature (Sullivan 2009). Propagation models typically consider specific weather and fuel conditions,and are aimed to simulate dynamic processes. To include the propagation potential in our fire risk assessment, we approached propagation modelling in a more structural way, by computing standard propagation conditions for worst-case scenarios. Fireline intensity (FI) was calculated for every pixel in the study site using the FlamMap model (Finney 2006). The FI is the amount of heat released per unit of fire front per second, and it can be related to the difficulty of containment of the fire (Rothermel 1983, table 4-1). The input variables for the model were: elevation, slope and aspect, extracted from the Digital Elevation Model of Spain (25-m pixel size); wind speed, taken from Spanish meteorological databases assuming worst-case conditions (95 percentile of daily wind speed series for the period 2002–06); upslope wind direction; fuel models, based on the NFFL classification (Rothermel 1983) and derived from the Spanish Fuel Models Map; canopy cover, extracted from the Vegetation Continuous Field product (MOD44B _C4_TREE.2005, Hansen *et al.* 2005); stand height, canopy base height and canopy bulk density estimated from expert opinion based on the Spanish Forest Map (200-m pixel size); and standard FMC values for dry conditions, based on fieldwork data (1-h fuels 5% FMC, 10 h 10% FMC, 100 h 12% FMC, live herbaceous 50% FMC and live woody 100% FMC).

Generation of input variables for fire vulnerability

Fire vulnerability included the evaluation of both socioeconomic and ecological potential damages. In previous projects (Chuvieco *et al.* 2010) we used a qualitative method to integrate different vulnerability factors, but further development makes it now possible to provide quantitative estimates based on monetary units (€ km^{-2}).

For this purpose we have calculated potential losses caused by fires as the reduction of value (marginal loss) that would occur when an area is burnt (Román *et al.* 2012). Because those losses remain a feature of the landscape until pre-fire conditions are restored, reduction of values was integrated throughout the estimated recovery time. As the importance of present values is higher than it is for future ones (future benefits tend to be considered more elusive), the equivalent present value of marginal losses was estimated through the application of a social discount rate. A discount rate value of 2% was selected as it is a common value in the economic valuation literature (Azqueta 2007). In order to avoid long-term effects becoming irrelevant, a hyperbolic factor was introduced in the marginal loss equation, so that the penalty applied to the future tends asymptotically to zero (Azqueta 2007). This is done by introducing the Neperian logarithm instead of the absolute number of years for recovery. In this way the present marginal loss *PML* was computed as:

$$PML = ML \times \frac{1 - (1 + r)^{-\log n_b}}{r} \quad (1)$$

where *ML* is the marginal loss, *r* is the discount rate (2%), and n_b is the estimated recovery time. Both *ML* and n_b were estimated at the same spatial resolution of our GIS fire risk system (1 km^2).

Obviously, the gravest effect of fires is the loss of human lives, and therefore this aspect should be taken into account for fire vulnerability assessment. However, because fire casualties are not linked to particular areas of the territory, it is very difficult to include this concept in spatial risk assessment, especially when trying to map spatial variations of vulnerability. Therefore, the direct effects of fires on human lives and property was focussed on the WUI, which is defined either as the contact between urban and forested areas, or where both are intermixed (Radeloff *et al.* 2005). WUI areas usually suffer the most severe damages during a fire, as recent cases in Australia, Russia, Greece and Southern California have shown. Additionally, WUI increases fire ignition probability, as many fires are caused by accidents or carelessness in these areas (Syphard *et al.* 2007).

We mapped WUI for the Spanish Peninsular territory based on the Corine Land cover map (Büttner *et al.* 2000). Urban areas were selected from Corine category 112: discontinuous urban fabric, which includes 'building, roads and artificially surfaced areas with vegetated areas and bare soil, which occupy discontinuous but significant surfaces' (Bossard *et al.* 2000), at the original spatial resolution of 1 ha. Neighbour analysis was performed to select only those areas that were closer than 100 m to trees or shrublands, which were considered a first approximation to the WUI for the whole country. The value of the WUI for each cell was computed from the house prices (€) of each municipality, whenever available, or the closest municipality otherwise. The total value of each cell was computed by aggregating WUI values of all 1-ha cells to the target grid size of 1 km^2. In this case, the marginal loss was not integrated through time (Eqn 1), as it is a one-time loss of capital.

The productive function of forests included the provision of wood, firewood, pine nuts, cork and pasture. The value of wood and firewood was calculated for each tree species and region as the product of its price and the production quantity. Pine nuts and cork production value was calculated by region by multiplying the production volumes and prices. Average productivities were computed from forest and bioclimatic maps, taking into account that potential production is constrained by technological, economic and ecological limits. A different market price approach was used for the valuation of livestock production. As the productivity of forests providing pasture decreases with the presence of trees and the competition of hunting population for food, the value was computed from rental price of shrub–grass area dedicated to pasture and a function of the canopy cover fraction (CCF), which varied regionally.

The recreational function of forest is quite complex to value in monetary units. The benefit transfer method was based on different published studies available for Spanish forested areas. Functions were adjusted based on the recreational services provided by a specific forest (€ km^{-2}), by finding relationships with the forest size, vegetation density (CCF, %), landuse class, observed demand (effective number of visitors) and self-consumption possibilities (represented by the population around the forest). Values provided by the literature are usually expressed as willingness to pay (WTP) per visit. They were

Table 2. Valuation method used in the socioeconomic vulnerability analysis

Variable	Valuation method
Property	Market prices
Wood	Market prices
Firewood	Market prices
Pine nuts	Market prices
Cork	Market prices
Pasture	Market prices
Recreational services	Benefit transfer
Big-game hunting	Market prices
Small-game hunting	Market prices
Fishing	Market prices
Carbon sinks	Replacement cost

converted into final values with data on the number of visitors and the area of each forest. Hunting and fishing values were computed from market prices and capture statistics available by autonomous regions.

The average accumulated biomass per species and region was computed using estimates of carbon stocks and forest maps (Montero *et al.* 2005). According to recent data, the price of an emission permit is ~35 € Mg^{-1} (http://www.pointcarbon.com/research/carbonmarketresearch/analyst/1.1414367 accessed March 2012), which we took as a basis on which to compute the value of carbon stock (€ km^{-2}). Table 2 summarises the different valuation methods used for the socioeconomic vulnerability analysis.

The ecological vulnerability was assessed in terms of the intrinsic value of the landscape and conservation areas. This component of the fire risk assessment considers intangible values, those that are not valued in market terms, but because of social interest in protecting particular areas due to their beauty, uniqueness or singularity. Conservation areas were extracted from the Spanish Ministry of Environment's database, which includes national and regional parks, natural reserves, Nature2000 network sites, European conservation sites and public forests. The intrinsic value of the landscape was based on five variables: geomorphology and land cover factors which together determine visual quality (Arriaza *et al.* 2004), singularity, representativeness and diversity. To compute the synthetic value of the landscape, a greater weight (50% more) was assigned to the conservation areas than to the intrinsic value.

Both the socioeconomic and landscape evaluation required estimation of the time needed for any cell of the study area to return to pre-fire conditions. Obviously, regeneration after fire is closely linked to ecological conditions of the affected area, and to fire propagation conditions, particularly fire intensity and residence time. The former was assessed spatially by analysing vegetation resilience, soil and climate conditions (Fig. 2). Resilience was characterised by structure (forest, shrubland or grassland) and reproductive strategy (resprouter or seeder). Both were derived from the Spanish Forest map (MMA 1997). Recovery time estimation was based on assigning an initial recovery time, considering optimal conditions for vegetation development. This base regeneration period was modified by

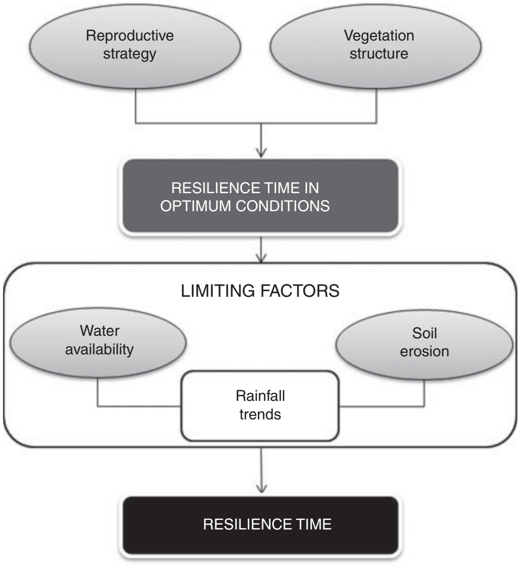

Fig. 2. Methodology for estimating resilience time.

taking into account the influence of vegetation growth constraints, i.e. water availability, soil loss and rainfall trends. The influence of water availability and soil erosion was introduced as a weight factor of the initial recovery time. In turn, seasonal rainfall trends, specifically winter and summer trends, were introduced by weighting water availability and soil loss. The overall procedure is summarised as:

$$RT = RTOC + T_{Fw}T_w + T_{Fe}T_a$$

where *RT* is the recovery time, *RTOC* is the recovery time in optimum conditions, T_{Fw} is the time increase from water availability, T_w is the winter rainfall trend weight, T_{Fe} the time increase from soil loss and T_a is the autumn rainfall trend weight. Once again it should be emphasised that this *RT* is not a category value, but an estimate of the time required to return to pre-fire conditions.

As stated above, in addition to vegetation characteristics, soil and rainfall conditions constrain the recovery of pre-fire conditions. We characterised structure and reproductive strategy of more than 500 species, assuming the revegetation process would occur under optimal conditions. This estimation was then corrected depending on water availability and potential soil erosion. The former was based on a biogeographical map (Rivas and Gandullo 1987) that classifies the country according to average rainfall conditions (arid, semiarid, dry sub-humid, humid and hyper-humid). The soil erosion analysis was based on the Pan European Soil Erosion Risk Assessment model (PESERA (Kirkby *et al.* 2004). This model quantifies water soil erosion at a European scale through a simple conservative erosion model, which is broken down into components that depend on climate, vegetation, soil factors and topography. The PESERA estimations of pre-fire erosion rates were modified using the ERMIT (Robichaud 2005) model, which integrates information on climate indicators, soil, topography, vegetation and fire severity, thus allowing simulations to assess the increase in erosion rates. Rainfall trends were extracted from de Luis *et al.* (2010), who computed the spatial variability of seasonal precipitation regimes in the Iberian Peninsula from 1946 to 2005. The estimates of the different components of fire vulnerability were based on worst-case fire propagation scenarios, considering maximum burn severity.

Integration methods

Once the input fire risk variables were generated, they were combined into synthetic fire risk components, following the risk scheme previously described. In order to do so, the input variables need to be converted to a common risk scale, and then be properly weighed. The most common methods to obtain common scales for risk integration are normalisation, qualitative categorisation and probabilistic approaches (Chuvieco *et al.* 2003). All fire danger input variables were converted to a common probabilistic scale (0–1) following the statistical logistic functions in the case of the human and lightning factors (see Fig. 3*a*, *b*), and a physical model to convert FMC to ignition probability (IP) based on the moisture of extinction (Chuvieco *et al.* 2004) (Fig. 3*f*). For the conversion of FI to propagation probabilities (PP) (0–1) the threshold values for fire suppression proposed by Rothermel (1983, table 4-1) were used. These FI values suggest thresholds that indicate whether a fire can be attacked with handtools alone, if mechanical equipment can be effective in fire containment, or if the fireline intensity is high enough that control efforts at the head of the fire are expected to be ineffective. The FI values obtained from the map were linearly interpolated from a PP of 0 for FI of 0 $kW\,m^{-1}$, increasing linearly within the thresholds (with $PP = 0.33$ for $FI = 350\,kW\,m^{-1}$ and $PP = 0.66$ for $FI = 1700\,kW\,m^{-1}$), and reaching a PP of 1 for pixels where $FI \geq 3500\,kW\,m^{-1}$ (Fig. 3*h*).

For the fire vulnerability components, the common scale for integration was the use of monetary units, which are easily interpreted by fire managers. The three components of our vulnerability assessment (houses and infrastructure, ecosystem services and landscape values), were computed in euros per square kilometre (Fig. 3*k*–*n*). As previously stated, this evaluation is simpler for those values with a market appreciation, but is more controversial when non-market aspects (cultural or ecological values) are considered.

Once the risk variables had a common scale, integration of the causative agents (human and lightning, Fig. 3*c*) was achieved using the Kolmogorov probabilistic rule (Tarantola 2005), which indicates the joint probability of two independent events. For instance, the IP derived from causative agents $P(Ca)$ was computed as:

$$P(Ca) = P(H) + P(L) - P(H) \cdot P(L) \qquad (2)$$

where $P(H)$ is the IP estimated for human factors and $P(L)$ is the IP estimated for lightning. The integration of IP of live and dead FMC (Fig. 3*f*) was performed by a weighted average of both IPs by the corresponding cover of dead and live fuels.

For the integration of IP related to causative agents and to FMC (named 'synthetic IP'), as well as for the combination of ignition and propagation probability (the 'integrated danger'), we used a multicriteria evaluation technique following experiences from previous projects (Chuvieco *et al.* 2010). Higher weights were used for the most dynamic components (related to FMC), as they changed daily or every 8 days, whereas human and lightning IP and propagation potential were assigned lower weights, as they were considered constant during the fire season.

The final fire risk was obtained by combining the integrated danger and the integrated vulnerability by means of a qualitative cross-tabulation method. A final two-digit number represents the fire risk, where the first digit corresponds to the fire danger, and the second to the vulnerability (see map legend in Fig. 3*q*). A look-up table was developed to show graphically the fire risk, with a green to yellow scale to represent danger (from 0 to 9), and light to dark green representing vulnerability (from 0 to 9). Red would imply high values of both danger and vulnerability.

Validation approaches

The validation of the fire risk system includes two phases. The first one focuses on the assessment of the input variables to determine whether or not they are accurately estimated, by comparing the results with actual measurements of each variable. The second one concerns the integrated indices, and it compares their estimated risk values with actual fire occurrence. Both aspects should be clearly identified, as underperformance of the risk indices may be caused either by inaccurate input variables (for instance, errors related to fuel maps or fire behaviour models) or inappropriate integration methods (giving a higher weight to a less relevant factor).

For this project, each input variable was validated against independent measurements (for instance FMC estimates were compared with field measurements), whereas the integrated indices were assessed against fire occurrence. Because some indices were associated with fire ignition and some to fire propagation, two indicators of fire occurrence were used: fire ignition points for the former, and burnt land maps for the latter. Ignition points were derived from Spanish fire statistics (compiled from fire reports), whereas burnt area perimeters were obtained from the European Forest Fire Information System (http://effis.jrc.ec.europa.eu/, accessed March 2012), using satellite images. Two different time series of validation data were used; one for dynamic variables (FMC for dead and live fuels and the integrated indices where FMC is included), which covered the fire season of 2010 (the last one available) and one for static variables (causative agent and propagation danger), which includes data from 2008 to 2010. Box plots and a non-parametric test (Mann–Whitney U) were computed to test significant differences between cells with and without fires.

Because fire vulnerability is an estimate of potential damages to socioeconomic and ecological assets, it cannot be validated either with ignition points or with fire perimeters. Estimates of actual damage caused by fires are not yet routinely collected in Spain, and therefore our estimates cannot be compared with

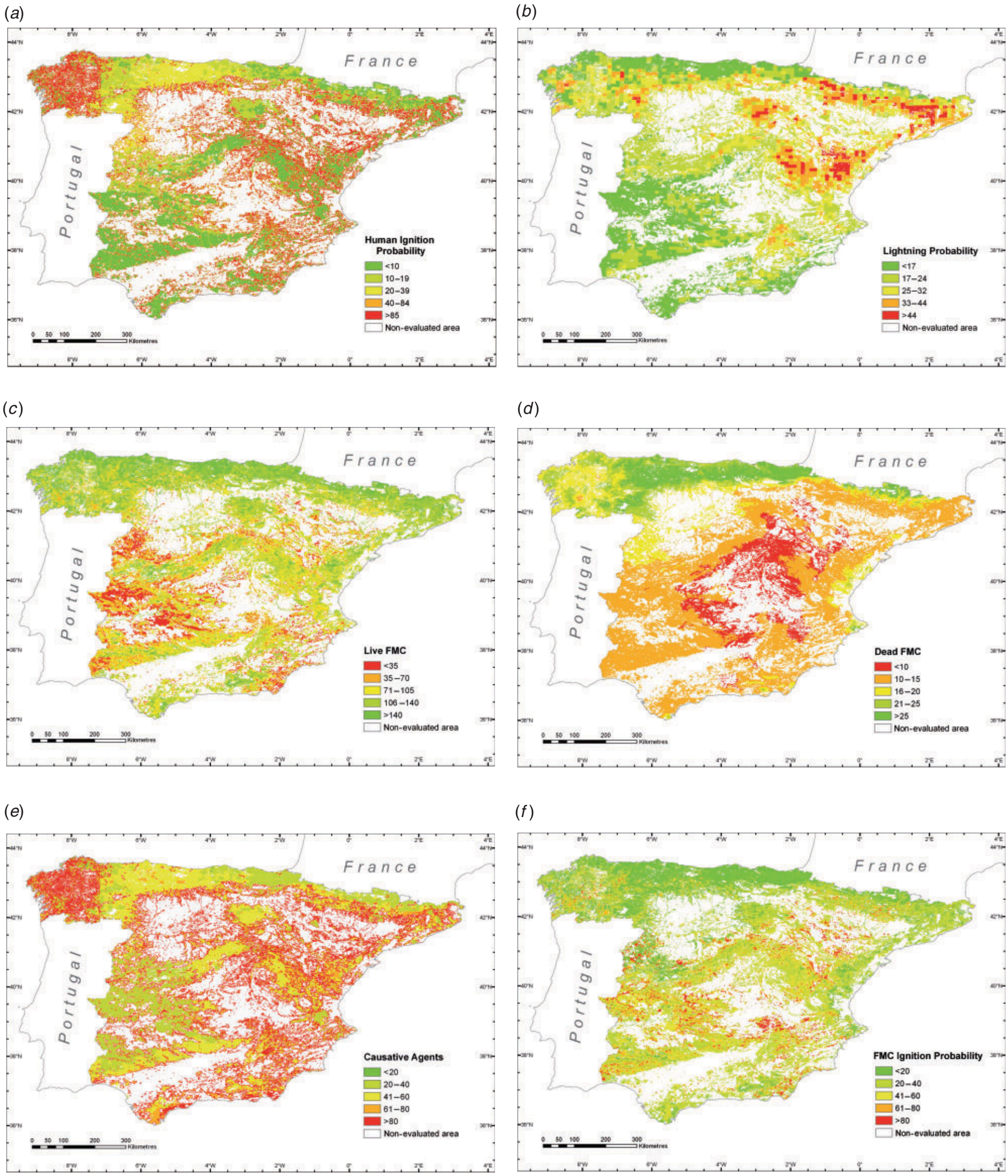

Fig. 3. Example of fire risk variables and integrated indices for 12 July 2011: (*a*) human ignition probability (IP), (*b*) lightning IP, (*c*) live FMC values, (*d*) dead FMC values, (*e*) IP from causative agents, (*f*) IP from FMC, (*g*) synthetic IP, (*h*) propagation probability, (*i*) integrated danger, (*j*) recovery time, (*k*) actual value of environmental services, (*l*) total value of environmental services, (*m*) houses and infrastructure, (*n*) ecological value, (*o*) socioeconomic value, (*p*) integrated vulnerability, (*q*) fire risk. Maps (*a–i*) represent the probabilities in percentages (values from 0 to 100). Blank cells refer to non-evaluated areas (non-forest categories).

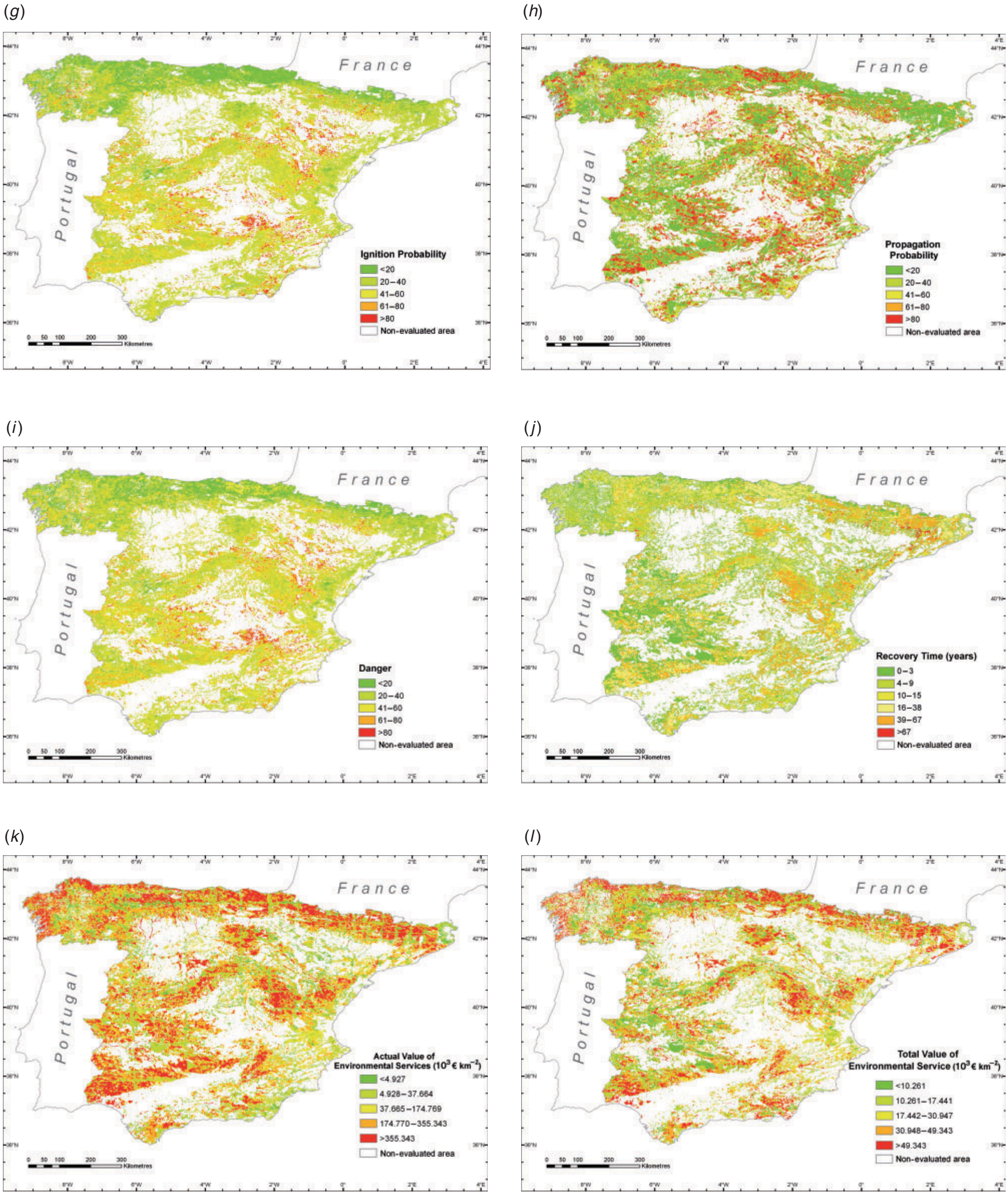

Fig. 3. (*Continued*)

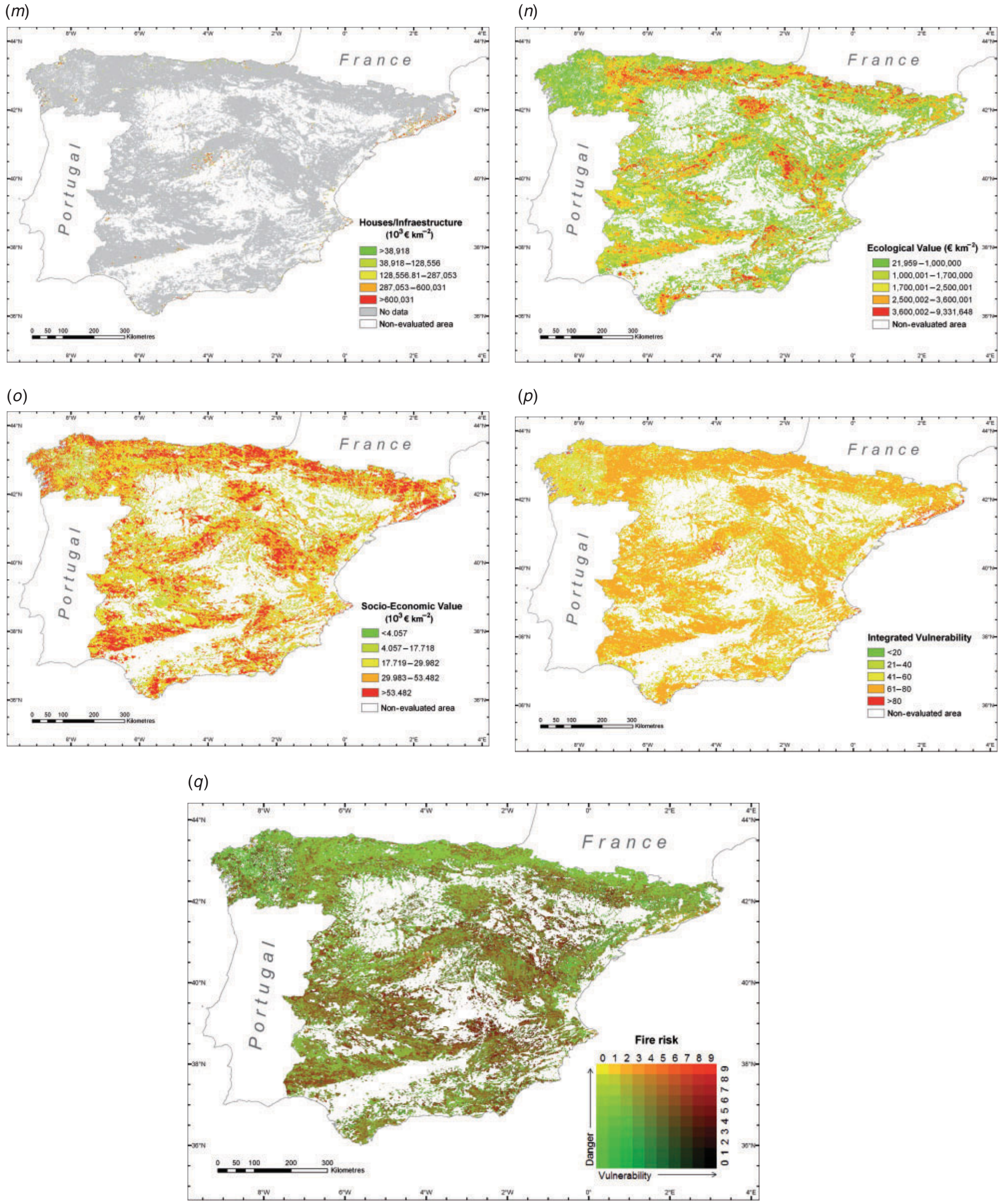

Fig. 3. (*Continued*)

other sources. However, the generation of the vulnerability layers was based on well-structured methods of economic and ecological analysis, as explained earlier.

Dissemination fire risk maps

Our project was designed to maintain a fluent collaboration with end users, who were mainly fire managers from the regional or national administration. To facilitate their interaction with the project outputs, a dedicated web mapping service was developed (http://www.fireglobe.es/, accessed March 2012), and included all the input risk variables and integrated indices. This service was tested during the fire seasons of 2010 (June–September) and 2011 (July–November) and was successfully evaluated by the end users. Furthermore, all the variables could be downloaded by end users through FTP (file transfer protocol). Two dedicated workshops were held with end users to analyse critically the performance and structure of the preliminary versions of the fire risk system.

Results

Validation of input variables

Fig. 3 shows an example for a single day during the summer of 2011 (12 July, which corresponded to medium–high danger conditions) of all variables generated to obtain the fire risk index, as well as the synthetic indices themselves. The modelling of the human-caused fires showed the importance of the crop–forest interface, particularly in the north-west and the borders of mountain areas. However, the WUI was found to be highly relevant in the central area (in the surroundings of Madrid) and the Mediterranean coast, where the urban sprawl is more evident. Both WUIs and crop–forest interface interfaces were the most explanatory according to the Student *t*-test ($P < 0.05$). The average local R^2 was 0.7, with a range between 0.19 and 0.85. The global agreement between estimated and observed human-caused fires was 87% (Table 3) with a kappa value of 0.73.

Regarding the 5198 lightning-caused fires, our model correctly predicted 63.5% of the calibration sample (60% of total number of fires) and 64.2% of the remaining 40% used for validating the model. The variables included in the model were number of strikes, climate types, and the DMC moisture code. Because the lightning strikes database covers only a brief period (2002–04), the model may be considered a preliminary one.

The estimation of FMC provided low RMSE values for live fuels (between 20 and 40%), higher values for grasslands (particularly when grass had high values of FMC) and lower for shrublands (Table 4). RMSE for woodlands had intermediate values. It is important to emphasise that errors were lower for drier fuels, which is very relevant for fire risk assessment, as lower FMC values are more related to fire ignition and propagation. The division between all samples and dry ones was based on the moisture of extinction (ME) for each fuel type, which is considered as the moisture threshold above which fire cannot be sustained (Rothermel 1972). In all cases, the systematic error (RMSEs) was lower than the unsystematic one (RMSEu), which implied that the error caused by the model performance and the predictor was lower than the error caused by uncontrolled factors.

Results from the fire vulnerability analysis suggested a recovery time for the Spanish peninsular ecosystem ranging from 2 years for grasslands to more than 67 years for tree-covered communities with low germination (Fig. 3*j*). However, there are significant contrasts in the geographical distribution of regeneration time, mainly among Eurosiberian and Mediterranean biogeographical regions. With regard to the economic valuation of the landscape, the lowest values were found in the north-western and interior ranges, foothills, coastal plains and some inland basins and depressions. The highest values were found in the northern alpine rangelands due to the presence of several natural protection areas and also to its high visual quality.

In terms of socioeconomic vulnerability, the most critical areas were found to be those at the WUI, because of the high values of houses potentially affected by fires. The WUI areas were mostly located in the vicinity of the largest cities (Madrid and Barcelona) and along the Mediterranean coast, a pattern that reflects the spatial distribution of the capital invested in real estate in continental Spain. The ecosystem function that will be most relevant in terms of potential losses is reduction of carbon sinks stored by forests. The next most relevant is loss of leisure opportunities in the environment provided by forests. Aggregated losses of timber and non-timber goods are less relevant in terms of economic values, but they have an important effect on local economies, as they are spatially more concentrated.

Validation of synthetic indices

The static variables (those not changing daily) showed less discrimination capacity than did dynamic variables. However, the causative agent, which was computed from human- and

Table 3. Outputs of the LGWR model for human-caused fires for the validation cases

Observed occurrence	Expected occurrence		
	High	Low	Total
High	31.4	11.5	42.9
Low	1.5	55.5	57.1
Total	33.0	67.0	100

Table 4. RMS errors for the estimation of live FMC (source Jurdao *et al.* 2012)

Region	Vegetation type	LFMC (%)	RMSE (%)	RMSEs (%)	RMSEu (%)
Eurosiberian	1.1	All	41.9	12.6	39.9
	Grassland	<200	30.6	3.6	30.4
	Shrubland	All	19.3	10.6	16.1
		<105	18.8	6.4	17.7
	Woodland	All	28.7	12.8	28.8
Mediterranean	Grassland	All	39.7	13.6	37.3
		<200	25.7	6.3	24.9
	Shrubland	All	26.8	17.2	20.5
		<105	22.8	11.3	19.8
	Woodland	All	27.3	15.4	22.6

Table 5. Mann–Whitney *Z* value and significant level found between dynamic danger indices and fire occurrence

Variable	Validation source	*P*	*Z*
Dead fuels ignition probability	Ignition points	<0.001	−28.529
Live fuels ignition probability	Ignition points	<0.001	−10.789
Integrated fuels ignition probability	Ignition points	<0.001	−17.087
Ignition danger	Ignition points	<0.001	−16.842
Integrated danger	Ignition points	<0.001	−15.424
Integrated danger	Burnt area perimeters	<0.001	−13.111

lightning-based ignition probability was found to be clearly associated with fire occurrence, showing significant differences between burnt and unburnt cells ($P < 0.01$). For propagation danger, differences were also observed, but they were not significant ($P > 0.36$).

For the dynamic variables, the ignition probability of the FMC was found to be highly significantly related to fire occurrence ($P < 0.001$), particularly for the dead fuels (Table 5). The integrated fuel ignition probability (including both live and dead fuels) was also found to be significantly related to ignition points, as well as ignition danger (causative agent and FMC) and integrated danger (ignition and propagation probability). It is worth noting that integrated danger was also found to be significantly related to burnt area perimeters ($P < 0.001$), which is in agreement with expected results, because integrated danger includes both ignition and propagation components.

Conclusions

This paper has presented a pre-operational fire risk assessment system that includes a wide range of variables related to the different components of fire risk. The system relies on GIT to provide a spatial evaluation of fire risk conditions, and it includes both danger and vulnerability components, offering a quantitative approach to model spatial variations of fire risk conditions. Conceptually, the system may be applicable at different spatial scales, from regional to global, depending on the availability of input datasets. The main novelties of the system are the integration of causative agents with moisture content of fuels and propagation potential, the quantification of values at stake, and the spatial assessment of fire risk conditions.

Preliminary validation of the integrated fire risk components shows expected trends, as the danger indices provided significant differences between the areas affected and non-affected by fires. Further efforts are required to extend this validation period to other fire seasons. Fire vulnerability components were not quantitatively assessed, because Spanish fire reports do not account for long-term damages. However, 10 fire managers attending a dedicated workshop where the whole fire risk system was assessed greatly appreciated the vulnerability information, as it helped them to better organise fire suppression resources.

Within this paper, two variables were modelled using a temporal approach (FMC of dead and live fuels), whereas others were considered static for the fire season. In future developments, we will try to model all variables in a dynamic way, including human and propagation factors, which will also affect the modelling of potential damages by providing more detailed estimates of fire behaviour conditions.

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APPENDIX B. METHODOLOGICAL APPROACH TO ASSESS THE SOCIO-ECONOMIC VULNERABILITY TO WILDFIRES

This appendix introduces the research work "Methodological approach to assess the socio-economic vulnerability to wildfires", an application example of the proposed method for quantitative assessment of ecological vulnerability, being an input to calculate the economic value of fire-affected assets.

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Methodological approach to assess the socio-economic vulnerability to wildfires in Spain

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ABSTRACT

The potential impacts of fire are spatially-dependent, according to the ecosystems, people and properties at risk. This study aimed to develop a methodology for the assessment of the socio-economic vulnerability to fire using Geographic Information Systems. We have conducted the vulnerability assessment by estimating the potential losses fire might cause during the time required for the recovery of the pre-fire environmental conditions.

We have considered that vegetation recovery time depends on the vegetation's structure, the reproductive strategy and the influence of constraining factors such as water availability, soil loss, fire frequency and fire intensity.

Regarding the socioeconomic values at risk, three categories of impact have been assessed. The impact on properties consisting of the potential destruction of build-up structures situated in the wild land-urban interface. The impact on people, i.e.: the probability of wildfires causing victims. The third category of impact embraces losses of environmental services because of the potential interruption of the productive, ecologic and recreational function of the affected ecosystems. Conventional economic valuation methodologies (revealed or declared preference techniques) were applied.

The application of the developed methodology to the case of continental Spain has resulted in several cartographic products (at a 1 km^2 resolution), thus presenting in a spatially explicit way the vulnerability of the territory to fire in different socio-economic aspects. According to the results, the average benefits derived from effective fire prevention measures because of avoided damages to properties, human life and ecosystems are 376,584 TEUR km^{-2}, 9.17 TEUR km^{-2} and 22.29 TEUR km^{-2}, respectively (TEUR = 1000 EUR).

1. Introduction

The Mediterranean region of Europe is strongly affected by forest fires, particularly Portugal, Spain, Italy, Greece and southern France. Although fires are an integral component of ecosystem dynamics of landscapes, uncontrolled fires may cause large environmental and economic damage. Recent changes in social and climate conditions, have significantly affected historical fire regimes, involving a greater potential damage than were traditionally the case. In Spain, the total area burned is decreasing, i.e. the annual average between 2000 and 2008 was around 125,000 ha, while in the period 1980–1989 it was almost 250,000; the number of fires is increasing: 18,150 compared to 15,300; and the economic losses do not present a clear trend: 271.43 compared to 267.96 million EUR (MARM, 1961–2011; Schmuck et al., 2009). In this sense, spatial assessments of fire risk aims to provide information helping to optimize the use of resources that societies devote to prevent and suppress fire, and to restore the affected areas, by determining protection priority areas.

Following the approach proposed by recent papers tackling fire risk assessment (Calkin et al., 2010; Chuvieco et al., 2010; Thompson et al., 2011), we distinguish between the probability of ignition and propagation, and the expected damages caused by fire. This latter component, termed vulnerability, is the scope of the present paper.

Several studies have evaluated the damages caused by fire after this it is over (Kent et al., 2003; Morton et al., 2003; Barrio et al., 2007). *Ex-ante* assessments are necessarily based on predictions on fire effects on the threatened assets and on estimations on their temporal extent. Once the resources at risk have been spatially localized, potential damages can be quantified, for instance, as the percentage net value change in terms of area depending on the fire intensity and resources' sensibility (Thompson et al., 2011). Alternatively, qualitative values can be assigned to those

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resources, according to the size and shape of the exposed areas (Kaloudis et al., 2005). Those options do not capture the willingness to pay (WTP) for the conservation of resources at risk.

Papers which have tried to predict and quantify in monetary terms changes in social welfare caused by wildfires have evidenced the high complexity of social perception of fire effects (Loomis and González-Cabán, 1998; Loomis et al., 2001; Kent et al., 2003; Morton et al., 2003; Loomis, 2004; Riera and Mogas, 2004; Barrio et al., 2007; Kaval et al., 2007). The tasks is further complicated by the existence of scientific uncertainties (Calkin et al., 2011).

Despite the limitations of economic valuation methods (Venn and Calkin, 2011), we adopted this approach to estimate the potential losses fire might cause, given that its results are easily understood and communicated across stakeholders, and can integrate multiple assets while keeping the overall coherence. Our estimation of the potential damages is based on the assumption that fire would affect the entire wildland surface and its interface with urbanized areas.

The results of this study may constitute then a valuable input for setting up priorities in protection areas, as well as showing evidence about the potential contribution of Geographic Information Systems to the decision making processes on forest management.

This paper is organized as follows. Section 2 describes the methodology and details the materials employed for its application to continental Spain. Section 3 shows the results and discusses their relevance and limitations. Section 4 states the main conclusions.

2. Materials and methods

This section presents the basis of the methodology followed to assess the socio-economic vulnerability of different ecosystems to fire in pecuniary terms (i.e. 2005 EUR).

To deal with the uncertainties associated with the extent of fire impacts, and adopting the precautionary approach, the worst-case scenario regarding the consequences on threatened buildings, population and ecosystems is assumed. The temporal dimension of damages to ecosystems was contemplated estimating the time span required until their total recovery under the most adverse conditions (n) and discounting the flow of services lost, which is considered to be constant. In order to limit the social penalty to the future (the ''tyranny of the present'') a hyperbolic discount factor (f) was applied, with a discount rate (r) of 2% (Pettenella et al., 2008):

$$f = \frac{1-(1+r)^{-\log n}}{r}$$

The temporal integration of the carbon stock loss follows a different logic. Taking into account that carbon is reabsorbed after fire during those years while forests regenerate, the overall impact consists of the difference between conserving the stock and losing it during a period of time. The social preference for the present implies that the present value of the recovered stock (obtained by applying the discount factor, f') is lower than the value of the stock lost today.

$$f' = \frac{1}{(1+r)^{\log n}}$$

The estimation of the annual flow of forest goods that are susceptible to be lost is based on effective productivities. These are computed as ratios of the annual production and the productive area. Depending on the particular good, different criteria have been employed to determine the productive area. This focus on the effective use of forests is the main difference with previously developed analytical assessment models, based on estimations on measures of the annual biomass increment. These reflect the potential use of forests instead (Mavsar et al., 2011a). In order to capture the net contribution of forests to social welfare, harvesting costs must be subtracted from prices (Mavsar et al., 2011b). When no reliable and site specific data on costs are available, prices corresponding to the closest point to each ecosystem may serve as approximation of the net value of forests productions.

The process comprised four consecutive steps: estimating the vegetation recovery time span; assets valuation; loss estimation and allocation. Finally, the results were aggregated at pixel level.

2.1. Estimating the vegetation recovery time span

To calculate the average time required for vegetation to recover its pre-fire conditions, we propose an innovative methodology which reflects the effect of fire on the recovery process. Due to the lack of spatial information about the forest's age, an initial recovery time (under optimal conditions for vegetation development) is assigned depending on the type of vegetation, and then increased by introducing the influence of vegetation recovery constraints: water availability, soil loss, fire frequency and fire intensity.

Initially, the recovery time was assessed according to the characteristics of the vegetal species appearing in the Forest Map of Spain (DGCN, 1997–2007) in terms of structure and reproductive strategy. As mentioned, it was considered that the re-vegetation process occurs under optimal conditions, i.e. without limitation factors such as lack of water or nutrients. The initial recovery time assignment is based on previous studies on post-fire regeneration and vegetation responses (Trabaud and Lepart, 1980; Tárrega and Luis-Calabuig, 1989; Trabaud, 1990; Vera, 1994; Trabaud, 1998; Trabaud, 2002; Pausas et al., 2004; Buhk et al., 2007; Baeza and Roy, 2008; Barbéro et al., 2008).

The initial recovery time was modified according to the information on water availability contained in the Vegetation Series map (Rivas and Gandullo, 1987). This map outlines areas of recognized vegetation units. Each of the different series presents a typical rainfall category (arid, semiarid, dry sub-humid, humid and hyper-humid) based on its annual precipitation. We assessed water availability by grouping those rainfall categories and assigning to each rainfall category a recovery time weight (Table 1).

The recovery time increment as a function of soil loss was evaluated by analyzing the distribution of soil erosion in post-fire conditions. The Pan European Soil Erosion Risk Assessment (PESERA) model (Kirkby et al., 2003) was used with this purpose. However, the erosion rates reported by PESERA model are calculated in pre-fire conditions. To take into account the erosion processes occurring after the high severity wildfires we developed different simulations of fire events using the ERMIT model (Robichaud et al., 2002) which led to the modification of the pre-fire erosion rates into post-fire ones through the calculation of its relative increment as a consequence of the loss of the vegetation protection cover. Once the erosion rates were corrected, we reclassified its values to assign the corresponding weights to the recovery time (see Table 2).

We assessed fire frequency from the data reported in the Spanish Fire Database 1988–2007. This database contains historical

Table 1
Rainfall categories and recovery time increment weight. *Source*: Self-elaboration.

Rainfall category	Precipitation (mm)	Time weight
Hyper-humid	>1600	1.00
Humid	1000–1600	1.05
Sub-humid	600–1000	1.10
Dry	350–600	1.25
Arid–semiarid	<350	1.50

Table 2
Post-fire erosion rates and recovery time increment weight. *Source*: Self-elaboration.

Post-fire erosion rate	Time weight
<0.04	1.00
0.04–0.13	1.05
0.13–0.36	1.10
0.36–0.86	1.15
>0.86	1.30

Table 3
Fire frequency categories and recovery time increment weight. *Source*: Self-elaboration.

Fire frequency	Time weight
No fire	1.00
Less than 2 fires	1.50
More than 2 fires	2.00

Table 4
Fuel availability and recovery time increment weight. *Source*: Self-elaboration.

Fuel amount (tonnes)	Time weight
<2.00	1.00
2.00–6.00	1.05
6.01–8.00	1.10
8.01–13.00	1.15
13.00–33.00	1.20

Table 5
Initial and maximum recovery time. *Source*: Self-elaboration.

	Initial recovery time	Maximum time
Grassland	2	9.36
Resprouter shrubland	6	28.08
Seeder shrubland	8	37.44
Resprouter tree	30	140.4
High seeding tree	35	163.8
Low seeding tree	45	208.9

data about each fire event during the recorded period. These records were then spatialized, and a fire frequency map was developed. Next, they were recoded into weights values, and used as the increase factors of the initial vegetation recovery time (see Table 3).

Finally, we carried out the assessment of fire intensity by assuming that this parameter depends mainly on the characteristics of the available fuel. With this purpose in mind, we recoded fuel categories reported in the Spanish Fuel Map (ICONA, 1991) into vegetation recovery weights (Table 4).

This procedure provides a map of vegetation recovery time, which is expressed in the number of years needed to restore pre-fire conditions, and that will be used later in the assets valuation process (Table 5).

2.2. Assets valuation

In order to discover the social value of a particular resource, different economic methods were applied to estimate the willingness to pay (WTP) of citizens for environmental services. Table 6 shows the level of aggregation and year of the Spanish data, together with the unit of measurement, and the variables employed to calculate average land productivities (expressed in EUR ha^{-1}).

Market prices appropriately represent the use value of buildings and forests products (food and raw material). For the case of Spain, official records reflect housing prices at municipal level. However, they do not contemplate centers of population having <25,000 inhabitants (http://www.fomento.gob.es/BE2/?nivel=2&orden=35000000). Having into account that location is a major factor in determining house prices, those in small municipalities, for which specific data is not available, are assumed to be similar to the closest municipality with data. The National Statistics Institute provided the municipal and province limits cartographic base (http://www.ine.es/ss/Satellite?L=0&c=Page&cid=1254735116596&p=1254735116596&pagename=ProductosYServicios%2FPYSLayout#a1259925031852).

For timber products, the most recent price according to the tree species was taken from official records (http://www.magrama.es/es/biodiversidad/temas/montes-y-politica-forestal/estadisticas-forestales/default.aspx and http://www.marm.es/es/estadistica/temas/anuario-de-estadistica/default.aspx). The high variability of non-timber products' volumes and prices makes it convenient to utilize interannual averages, in order to appropriately reflect the average ecosystem's performance. In the case of Spain, estimated average productivities reflect real and sustainable extraction, because effective production does not undermine the ability of ecosystems to continue to provide such volumes in the future. The potential productivity of Spanish forests is underutilized as a result of the low profitability of extractive activities (MMA, 2000). Cartographic products provided the spatial information required to determine productive areas for each product. The Spanish Forest Map (MFE200) was used to compute potential productive areas according to species occupation, i.e. areas occupied by the main species in monospecific forests, and by the two main species in mixed forests (DGCN, 1997–2007). From this data, we selected the effective productive areas according to its Canopy Cover Fraction (CCF, between 20% and 80% for cork production); its phenological stage - at timber and pole-stage for timber products; at pole-stage for non-timber products – (DGCN, 2004); its protection status – outside National Parks, with the exception of *Monfragüe* and *Cabañeros* for the production of pine nuts and cork -; and its slope (IGN, 1992–1997), assuming that above 35% extractive activities with commercial purpose (as it is the case of timber and non-timber goods contemplated in this exercise) become unfeasible (Pettenella et al., 2008).

Table 6
Valuation methodology summary table. *Source*: Self elaboration.

Type of impact	Valuation method	Original unit	Aggregation level	Year[a]	Variables required for conversion into EUR ha^{-1}
Buildings	Market price	EUR ha^{-1}	Municipality	2009	–
Wood/firewood		EUR m^{-3}	Tree species	2006	Annual production and productive area (provincial)
Cork/pine nuts		EUR kg^{-1}	National	1985–2007	Annual production and productive area (national)
Hunting/fishing		EUR	Province	1996–2007	Productive area (provincial)
Recreational services	Benefit transfer	EUR visit	Natural area	1996–2009	Annual visits and recreational area
Carbon stocks	Replacement cost	EUR ton^{-1}	National	2010	Stock and occupied area (by species).
Population	Hedonic salary	EUR individual^{-1}	National	2003	Annual victims and burned area

[a] We chose the last data available apart from those cases in which an interannual average is more representative.

Market prices reflect only one part of the utility derived from hunting and fishing: the (consumptive) value of bushmeat or fish, but not that derived from the pleasure of practicing these activities. Because of the lack of studies estimating recreational values of hunting and fishing in Spain, we assumed that the annual revenues of hunting and fishing facilities represented the minimum WTP for conserving the opportunity to practice these activities, and used the already referenced official records. We identified productive areas by establishing a correspondence between land use classes (according to the MFE200) and habitats for wildlife populations: croplands and spaces with little or no vegetation for small-game hunting species; forests and scrublands for big-game hunting species; rivers for ichthyofauna.

Regarding the amenities provided by natural areas, previous studies provided the basis to estimate the value of leisure opportunities which are not traded in markets. In the particular case of Spain, there were 41 estimates on the WTP for visiting protected areas exposed to wildfire risk (Voces et al., 2010). They were converted into spatial units by multiplying by the corresponding rate of number of visitors/area using official statistics and maps of the protected sites provided by EUROPARC España (http://www.redeuroparc.org/bases_datos.jsp), the Spanish National Parks Network (http://reddeparquesnacionales.mma.es/parques/index.htm). When no primary specific estimate was available, average values by land use class from a previous work were directly transferred (Esteban, 2010). These values came from a meta-analysis aimed to find the specific function explaining estimates on WTP with theoretically explicative variables (i.e. forest size, number of visitors, vegetation density and number of inhabitants in the surroundings).

As it is usually done in the literature (Alexandrian et al., 2005; Pettenella et al., 2008; Mavsar et al., 2011b), we employed the replacement cost method in order to value the carbon stock contained in the biomass at risk. This method consists of estimating the cost of neutralizing the release of one ton of carbon. Carbon market price (35 EUR ton^{-1}, according to Point Carbon, http://www.pointcarbon.com/polopoly_fs/1.1420234!Carbon%202010.pdf) indicates this cost, as it represents the compensation demanded by companies investing in mitigation (e.g. through the Clean Development Mechanism). To calculate average productivities (as value/area ratios), the stock susceptible to be released received a different treatment depending on its duration. The part of the stock which is extracted and transformed into wood products, retains carbon during a period of time that depends on the final use of these products (Bateman and Lovett, 2000). We computed then the present value of this temporal stock, to aggregate it to the value of the stock remaining on the standing forest.

In the case of Spain, estimations on both standing and extracted stock by tree species are available (Montero et al., 2005). The weight of each timber product in relation with the total annual production is calculated with data taken from the official statistics. Interannual averages of these weights are used to apply the different retention periods to their corresponding share of the extracted carbon stock (Table 7). The occupation by species was computed using the MFE200.

Table 7
Wood products' weights. *Source*: Self-elaboration.

Wood products	Weight (%)
Sawmill	35
Board	22
Wood pulp	32
Fuel	1
Fence posts/pole	3
Other	7

The Value of a Statistic Life (VSL) is meant to reflect the contribution to social welfare derived from avoiding one mortal accident and amounts to 2.35 million EUR_{2003} in the Spanish case (Riera et al., 2007). We converted this figure into spatial terms by applying the accident rate, i.e. 0.0000502 victim ha^{-1}, calculated from the official statistics (http://www.mma.es/secciones/biodiversidad/defensa_incendios/estadisticas_incendios/index.htm#3).

Following these steps, we could estimate the value of the services provided by the assets at risk, together with the benefits associated to preventing the loss of life in terms of monetary units per hectare. The next step was to estimate how much of these values would be lost as a result of fire.

2.3. Estimation of the social loss

Experts estimate that under very high fire intensity conditions, residential locations might lose approx. 80% of their value (Thompson et al., 2011). However, in each particular case, the extent of the damage depends on the exposure conditions and the landscape fuel treatments, among other factors. In the worst case scenario, fire would entail the loss of 100% of the value of built structures located within the area at risk. However, fire would not affect to this extent land value. Therefore, when housing prices include it (as it is the case), damage estimation requires to subtract from the value of the house the part corresponding to the land. We employed official statistics on land prices with this purpose, which are aggregated by municipality size and province (http://www.fomento.gob.es/BE2/?nivel=2&orden=36000000). The extent of the loss depends also on number of floors, levels, present at the house. We presumed that a construction close to the wildland had an average of two floors.

The overall response might, however, be less adverse than the initial one, and potential losses do not always coincide with effective ones (Thompson et al., 2010). For instance, the affluence of hunters may abruptly diminish after fire, even when fire has only partially affected fauna's ability to reproduce. For the case of Spain, concrete estimates of loss coefficients for several environmental services and fire intensity levels (Rodríguez et al., 2009) were available. In case of the higher level (VI) wood would depreciate a 90%, fruits a 75% (i.e. pine nuts), fishing a 45%, and both cork and hunting a 100%. For the remaining services (firewood, recreational services and CO_2 sequestration), a 100% of loss was assumed.

The magnitude of the loss also depends on the ecosystems' ability to naturally recover its pre-fire conditions. Therefore, the overall loss was computed as the capitalization of the estimated losses occurring annually until the complete recovery. During the regeneration period, forests gradually recover carbon stocks. Social preference for the present implies that the value attributed to the stock in the future is lower than the value of the stock lost because of the fire. Therefore, the net loss is equal to the difference between both values.

In some cases, society can recover one portion of the affected resources' value immediately after the fire. We did not find evidences of residual values for the case of Spain, with the exception of burned wood. This can be sold at the 42% of its ordinary price (Barrio et al., 2007). Therefore, we subtracted this portion from the loss associated to the first year.

The next step was to determine where those losses take place. For this purpose, we used Geographic Information Systems (GIS) to map results at 1 km^2 spatial resolution.

2.4. Allocation to the territory

Damages to building occur in high exposed areas, usually referred to as the wildland-urban interface or WUI. We defined the WUI as those built-up areas, i.e. category "112. Discontinuous urban fabric" in the CLC (EEA, 2010) situated within a radius of 100 m from woodlands and scrublands (DGCN, 1997-2007).

Because of the lack of evidences of the relationship between mortal accidents occurrence and land features in the case of Spain, we allocated this loss homogeneously to the forested area (DGCN, 1997-2007).

Losses of environmental services are allocated to those areas providing them. Given that the estimated loss of non-timber products was homogeneous, we allocated it proportionally to vegetation density (Hansen et al., 2003).

After the computation process we examine the distribution of resulting values and detected extreme values at the right side of the density plot. These deviations, caused by topological errors in the original layers, did not represent a significant share of the aggregated value, but distortion the average marginal values. In order to avoid this effect we corrected those pixels by giving them the value of the percentile 99. Finally, a measure of the socioeconomic vulnerability was obtained by adding the different types of losses occurring within each pixel of the map.

3. Results and discussion

Fig. 1 shows the potential losses associated to damages to buildings. As expected, losses are highly concentrated around the most economically relevant cities (Madrid and Barcelona) and along the coast, something that reflects the spatial distribution of the capital invested in real estate in continental Spain.

Fig. 2 shows the different recovery times expressed in years. Results show significant contrasts in the geographical distribution of regeneration time (mainly among Euro-Siberian and Mediterranean bio-geographical regions), ranging between 2 years for grasslands to around 200 years for tree-covered communities with low germination. The higher recovery times are located in the Mediterranean region, mainly related with low water availability due to little rainfall, and also to the climatic aggressiveness of this area, which produces relatively frequent torrential rainfall events thus increasing soil loss. However, high recovery times are also found in the Euro-Siberian region where the higher fire frequency has been registered during the last 25 years in Spain.

Fig. 3 shows the potential loss associated to the disappearance of services provided by ecosystems to society during the time their functions are affected. This loss is made of the provision of products

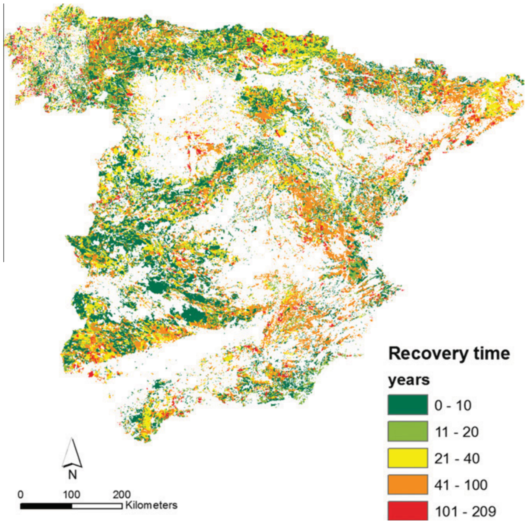

Fig. 2. Recovery time.

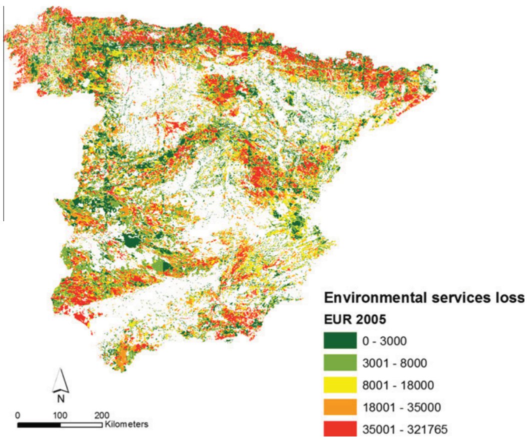

Fig. 3. Environmental services loss.

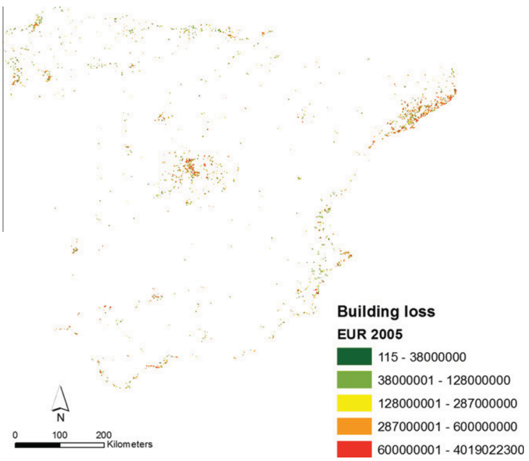

Fig. 1. Building loss.

(wood, firewood, cork and pine nuts), recreational services (including hunting and fishing) and the temporal destruction of the carbon stock contained in the forests' biomass. Major losses of environmental services are located in the North of the Peninsula. The high value of CO_2 stocks and wood production at risk explain the losses in the provinces of *Galicia*, *Asturias*, *Cantabria*, *País Vasco*, *Navarra*, the North of *Aragón*, *Cataluña* and *Castilla*. Losses in *Almería* are associated with recreational services. Huelva houses also relevant losses in concept of CO_2 stocks. Values in the Mediterranean region are influenced by long recovery periods.

There is no point in showing the map regarding the loss of human lives, because its spatial distribution is equal to the one of forested areas, as a consequence of the allocation process. Fig. 4 shows the socio-economic loss, which consists of the integration of the losses in concept of buildings, environmental services and

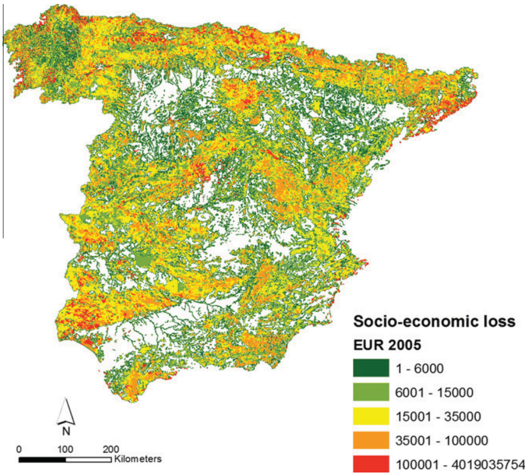

Fig. 4. Socio-economic loss.

Table 8
Losses by type of impact. *Source*: Self elaboration.

Type of impact	Average (TEUR km^{-2})	Aggregate (TEUR)
Buildings	376,584	2,400,346,504
Wood	6.28	345,001
Firewood	0.80	9779
Cork	48.36	241,822
Pine nuts	3.40	26,137
Big-game hunting	0.23	56,230
Small-game hunting	0.47	97,648
Fishing	1.81	11,851
Recreational services	3.71	687,596
CO_2 stock	20.53	4,054,930
Human life	9.17	3,457,950

human lives. The spatial variability of the vulnerability is majorly influenced by the threat to buildings and carbon stocks.

Table 8 summarizes the results for each category of impact. According to them, the most vulnerable areas are WUI, where wildfire would produce an average loss of approx. 377,000 TEUR per hectare (or 188.29 EUR m^2, as we assumed buildings in the WUI to have two floors). This amount is the 20% of the average housing price within the Spanish territory, once subtracted the land price (Fundación_BBVA-Ivie, 2009).

Avoiding the risk of victims in areas exposed to wildfires would be perceived as a gain of social welfare accounting, at least, for 3,457,950 TEUR in the whole territory.

The damage on ecosystem services that would entail the highest loss is the ecological function performed by the biomass retaining carbon from the atmosphere (4,054,930 TEUR). Next in relevance is the loss of leisure opportunities in the environment provided by forest, including hunting and fishing (853,325 TEUR). The damage on the productive function of forests accounts for 622,739 TEUR. Average losses by area reflect the concentration of losses associated to forests' goods as cork, wood and pine nuts. When comparing these results with the *ex-post* estimation of economic losses caused by fires in Galicia in 2006 (Barrio et al., 2007) and in the whole Spanish territory in 2010 (MARM, 1961-2011), several conclusions may be drawn. Due to the high productivity of the forested areas in Galicia – they produce more than the 50% of the total production of wood (MMA, 2007) – even though long term effects were not contemplated in the losses assessment, these account for approx. a 23% of the estimated damage on the productive function of the Spanish forests. According to the official estimations, wildfires in 2010 caused a loss in this concept equivalent to the 12% of the estimated damage. Regarding the recreational function, the short term losses account for a 2% of the estimated damage in both cases of reference (Galicia, 2006 and Spain, 2010). In Galicia the impact derived from the loss of carbon sequestration capacity represents an insignificant share of the estimated damage due to the shorter period (five months) and the lower carbon price (16.15 EUR ton^{-1}) employed in the assessment. Resources destined to the Wildfire Defense Area represent a limited share of the potential losses fire might cause in the worst case scenario. For instance, in 2011 the budget accounted for the 1% of the estimated losses.

Carrying out large spatial scale assessments, as the one presented in this paper, involves a series of assumptions which simplify reality. Housing was treated as a quasi-homogeneous good, assuming its market price depends on the size of the town and the distance from centers of population. Apart from this simplification, market prices may not appropriately reflect housing use value, as a result of the high complexity of this particular market.

We have also assumed that changes in the supply of different commodities caused by fire would not be big enough to change prices. However, for the particular case of wood, the flooding of markets with salvaged timber can suppose an economic disequilibrium in the short run (Mavsar et al., 2011b).

Different improvements of this methodology can be identified. Wood extraction costs may prevent extractive activities on remote sites; therefore the economic feasibility is a factor to be taken into account when identifying productive areas. This is possible in those cases where a detailed cartography of roads and trails provides the basis to introduce the distance to roads as a value criterion (Pettenella et al., 2008). Benefit transfer might not accurately reflect social preferences. Experts recommend regional choice modeling studies in order to overcome this limitation (Venn and Calkin, 2011).

Future assessments might also contemplate additional impacts. For instance, impacts on infrastructure, on further non-timber products, on non-consumptive values derived from hunting and fishing, on the ecological role of ecosystems and on the increase of mortality rates because of particulate matter emissions. Alternative analytical assessment models provide procedures to evaluate impacts associated to soil erosion and biodiversity loss (Mavsar et al., 2011a; Mavsar et al., 2011b). The Uniform World Model would provide the basis to measure this latter impact in monetary units, by considering each forest as a fixed emission source (Spadaro and Rabl, 2002).

4. Conclusions

In many countries, the public sector is responsible for wildfire prevention and extinction. In order to ensure the efficient use of resources, public managers need spatial information on the potential consequences of fire.

This paper presents and applies a methodology designed to generate a spatially explicit index satisfying such needs. The main output of its application is to present the benefits derived from effective prevention strategies in monetary units, thus facilitating the comparison of different alternatives to prevent fire and the establishment of priority areas.

The precautionary approach adopted here allows coping with the limited understanding of the natural resources' response to fire, and of the subsequent social perception. Results should be interpreted as the social monetary benefits (losses) that, without consideration of non-use value of ecosystems, would entail the effective (failed) prevention of high intensity wildfires.

Results reflect the relevance of ecosystem services provided by forests other than the production of goods, which are those with an existing market value. Besides, they also reflect the monetary relevance of marketable assets as buildings.

The proposed methodology is portable to other regions while the required variables are few and representative. Official statistics usually provide time series on housing prices. Cartography on land cover types (e.g. CORINE Land Cover 2006 raster) serves as basis for the WUI localization. Time series of the annual number of victims and the burned area, a regional specific estimation on the VSL (or, alternatively, on the WTP to save one anonymous person's life) and cartography of the forested areas constitute the data requirements for the estimation of the potential damage to population. The cartographic products required for the recovery time span would contain data on the vegetation structure, the reproductive strategy, the water availability, the erosion rates (e.g. PESERA), the fuel availability. The fire frequency calculation requires regional time series of wildfires. Time series of prices (or incomes) for forests goods (e.g. FAOSTAT trade statistic database), together with cartographic products of the different factors influencing land ability to provide each forest good (tree species occupation, CCF, phenological stage, protected areas, slope) allow the calculation of spatial specific productivities. Site specific values of the WTP for visiting protected areas (together with site specific time series of the annual number of visitors and protected sites' maps), and estimates on the value attributed to the recreational use of forested areas are required for the inclusion of this environmental service in the vulnerability assessment. The Cost of Policy Inaction initiative (COPI) provides regional estimates susceptible to be used for value transfer purposes (Braat et al., 2008). They also provide data on the carbon sequestration capacity by forest type, which together with the international price of carbon emission allowances (e.g. www.pointcarbon.com or www.wndscarbonoffsets.com) constitute the data requirements for the valuation of this environmental service. The damage level for each category of impact can be provided by experts.

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APPENDIX C. LAND COVER CHANGE AND FIRE REGIME IN THE EUROPEAN MEDITERRANEAN REGION

This appendix extends the results for fire trends in number of fires and burnt area size, as well as presents a brief assessment of wilfires as a driving factor of land-cover change at European scale.

Chapter 2
Land Cover Change and Fire Regime in the European Mediterranean Region

Jesús San-Miguel-Ayanz, Marcos Rodrigues, Sandra Santos de Oliveira, Claudia Kemper Pacheco, Francisco Moreira, Beatriz Duguy, and Andrea Camia

2.1 Introduction

Although fire is an integral component of Mediterranean ecosystems, the dynamics of fire regimes in Southern Europe is driven mainly by human factors. In fact, humans are responsible for over 95% of the fires taking place in this region (San-Miguel Ayanz and Camia 2009). Traditional usage of fire in agricultural and cattle raising practices in the region is one of the main causes of forest fires. Demographic changes related to the abandonment of rural areas are also related to increased fire hazard. Fuel accumulation due to the lack of forest management practices in the region leads to uncontrolled forest fires. Although, overall, the rural population in Southern Europe has decreased, peaks of high population density in recreational wildland areas during holiday periods increased fire ignition in

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summer months. This is further enhanced by the expansion of urban areas into wildland areas. This effect, which is due to either the expansion of cities or the construction of secondary houses in rural areas, has lead to an extended Wildland Urban Interface (WUI) in the region. The difficult fire management of the extensive WUI in Southern Europe has been the cause of catastrophic fires such as those in Portugal in 2003 or Greece in 2007.

Land cover is a fundamental component of fire dynamics. It influences all the phases of the fire, from ignition to fire behavior and post-fire restoration. The analysis of land cover changes in the last decades is tackled in the first section of this chapter. This is followed by the analysis of fire regimes in the region, both in terms of number of fires and burned areas. The last two sections of the chapter are dedicated to an in depth analysis of land cover changes in areas affected by fires and the effects of fire on land cover dynamics.

2.2 Overview of Land Cover Changes in Europe

Land cover changes are related to fire hazard through changes in fuel load which, along with topography and weather, are the main drivers of fire intensity and rate of spread (Fernandes 2009; Moreira et al. 2009; Rothermel 1983). Thus, increased fire hazard is expected where land cover changes promote an increase in plant biomass (fuel load) while decreased fire hazard is linked to changes associated with the removal of biomass. The CORINE Land Cover database (http://www.eea.europa.eu/data-and-maps) was used to analyze the changes in land cover in southern Europe between 1990 and 2006. The analysis was carried out in 4 out of the 5 European Mediterranean countries that are most significantly affected by forest fires, i.e. Portugal, Spain, France and Italy. Greece was excluded from this analysis due to the lack of CORINE 2006 data for this country.

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CORINE provides a thematic legend of 44 land cover classes grouped in three hierarchical levels. These land cover classes were grouped into six general categories: Urban, Artificial, Agriculture, Forest, Shrubland, and No-vegetation. The analysis of transition of areas among these categories was carried out.

The largest land cover change observed was the transition from forests to shrublands (over three million hectares) (Table 2.1), which could be interpreted as forest degradation due to several causes (e.g. logging, fire, drought). Forests have also been replaced by urban, agricultural, artificial areas and areas with no vegetation. There were also significant areas of shrublands that have been replaced by agricultural areas (over one million hectares), areas with no vegetation, artificial and urban areas. All these changes contributed to decrease fire hazard.

On the other hand, a significant proportion of shrublands have become forests (over two million hectares) and the transition of former agricultural areas to forests (over 800,000 ha) and shrublands (over one million hectares) has also been significant. The transition of areas with no vegetation to shrublands was also relevant (over 450,000 ha). These changes are probably the consequence of secondary succession in shrublands and abandoned agricultural fields, along with afforestation programs promoted by EU agricultural and forest policies during the study period.

A large number of regional studies have also provided evidence of increased fire hazard in the Mediterranean areas in the last decades, mainly due to the increased cover of forests and shrublands in areas with former lower fuel loads. For example, Van Doorn and Baker (2007), in a region of southern Portugal, registered a 75% decline in the area of agricultural fields during the period 1985–2000, and an increase in shrublands and forest plantations. Similarly, Falcucci et al. (2007) measured a 74% increase in forest cover in Italy during the period 1960–2000, and a 20% decrease in agricultural areas.

The balance between land cover changes promoting an increase in fire hazard (summing 4.9 million hectares) and the ones decreasing it (5.4 million hectares) would suggest that southern Europe has become less fire prone in the period 1990–2006. These results are in line with those presented in the analysis of land cover changes during the period 1990–2000 in 24 European countries by Feranec et al. (2010). These authors also found that the establishment of forests by planting or natural regeneration provoked a significant proportion of land cover transitions corresponding to an increased fire hazard, as they result in an increase in fuel load at the landscape level. The authors concluded that afforestation was the most prominent land cover flow across all Europe, during this time period, particularly in Portugal, Spain and France. In contrast, three flow types – deforestation, intensification of agriculture and urbanization/ industrialization – included several transitions associated to decreased fire hazard. The greatest losses in forest have been observed in Spain, France and Portugal, mainly because of disturbances such as fire and wind. In the countries of Southern Europe, intensification of agriculture was more prevalent in Spain, whereas urbanization processes were more extensive in Spain, France, Italy and Portugal (Feranec et al. 2010).

Table 2.1 Changes (in hectares) among land cover classes from 1990 to 2006 in Mediterranean Europe (Portugal, Spain, France and Italy)

	To 2006	Urban	Artificial	Agricultural	Forest	Shrubland	No vegetation
From 1990	Urban	11,012,514	75,795	197,427	**11,957**	**5,897**	723
	Artificial	70,972	2,826,169	107,870	**21,353**	**62,476**	7,292
	Agricultural	1,220,019	765,940	180,616,767	**815,487**	**1,188,775**	25,636
	Forest	*43,099*	*101,413*	*583,320*	85,029,222	*3,192,178*	*82,721*
	Shrubland	*44,331*	*99,291*	*1,071,732*	**2,299,768**	26,980,642	*199,171*
	No vegetation	3,362	12,183	57,788	**43,162**	**468,750**	4,120,242

Note: Changes associated to significant increases in fire hazard are signaled in bold, whereas changes leading to major decreases in fire hazard are in italics

2.3 Overview of Changes in Number of Fires and Burned Area in the European Mediterranean Countries

The Mediterranean region of Europe is strongly affected by forest fires. According to European Statistics (EC 2010), from 1980 until 2009 fires have burned an average of circa 478,900 ha of land per year in the five Southern European countries most affected by fire (Portugal, Spain, France, Italy and Greece). Data on the number of fires and burned area in this region have been collected since the 1980s by each country and compiled in the European Fire Database (Camia et al. 2010). The analysis of the spatial and temporal trends of fires is crucial to understand the underlying causes of the fires and their environmental and socio-economic impacts, assuming a key role in fire prevention and management. The purpose of this section is to analyze the spatial and temporal trends of fire frequency (number of fires) and burned area size, two essential components of the fire regime of an area.

The analysis of the number of fires, total burned area and average fire size was carried out at different spatial levels:

- At regional (supranational) level, considering the Euro-Mediterranean region as a whole, with the purpose of characterizing its fire regimes, known to be markedly different from the rest of Europe. The region under study, shortly referred to as EUMed in what follows, comprises Portugal, Spain, France, Italy and Greece;
- At country level, by analyzing the data of each country individually in order to assess differences between countries that may depend on national settings and policies;
- At province level (NUTS3), to investigate the potential influence of local environmental and socio-economic conditions.

Temporal trends were analyzed separately for the whole study period (1980–2009) and for the last 10 years (2000–2009). These trends were compared using the Mann–Kendall test, a non-parametric statistical test used to identify trends in time series data (Kendall 1975). In addition, seasonal trends were also characterized both at regional and country levels, by examining separately the months corresponding to the main fire season (June to October) and the other months.

2.3.1 Overall Trends for the EUMed Region

The general trend for the whole study period was a slight increase in the number of fires (Fig. 2.1), even though annual fluctuations are evident. In the 1990s a substantial increase was observed, while in the last 10 years (since 2000), the number of fires decreased, except for the years 2003 and 2005. The increase observed in the 1990s can be partly due to the changes in the reporting systems in the countries, mostly driven by EC regulations. Other reasons for the rise in the number of fires

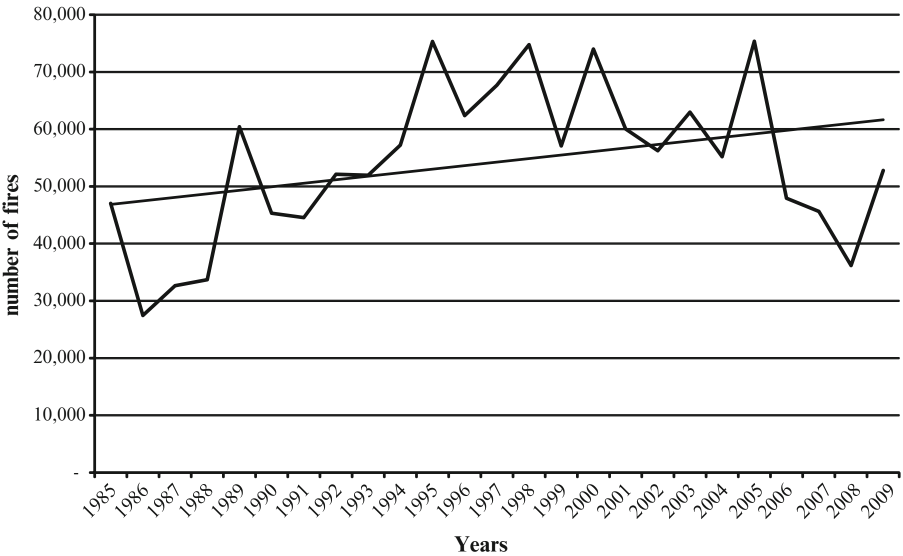

Fig. 2.1 Total annual number of fires in the EUMed region from 1985 until 2009, and resulting trend line

during this period may be associated with fuel accumulation related to land cover changes such as the expansion of shrublands and abandonment of agricultural lands (Carmo et al. 2011; Lloret et al. 2002; Romero-Calcerrada et al. 2008). The results of the Mann–Kendall test showed that, for the entire study period, the general trend is an increase, but not significant ($S=64$, $P=0.14$). For the last 10 years, on the contrary, a significant decreasing trend was observed ($S=-25$, $P=0.032$).

The burned area, on the other hand, showed a decreasing trend since 1980, with strong annual fluctuations (Fig. 2.2). The results of the Mann–Kendall test show that, for both periods, the general trend was a decrease, but significant only when considering the entire time series ($S=-88$, $P=0.042$). Besides the influence of weather conditions in fire spread and burned area annually, this decrease is likely related to the implementation of fire prevention strategies and to the improvement in fire detection and fire-fighting techniques observed during the last years.

2.3.2 Overall Trends by Country

The countries of the EUMed region showed different trends concerning the number of fires (Fig. 2.3).

Comparing the entire time series with the last 10 years, different trends can be observed depending on the country (Table 2.2). Portugal, Spain and Greece showed an increasing trend for the whole study period, while France and Italy had a general decrease.

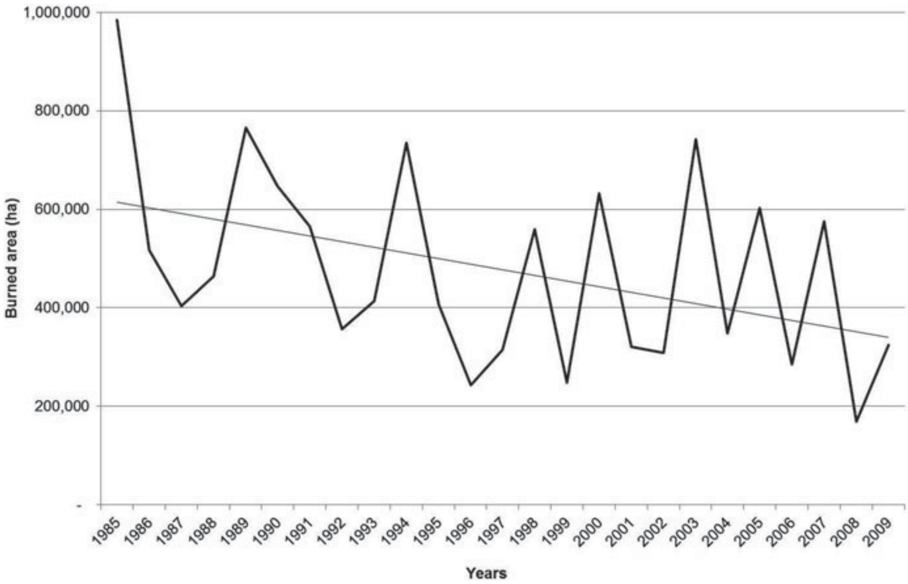

Fig. 2.2 Total annual burned area (ha) in the EUMed region from 1985 until 2009, and resulting trend line

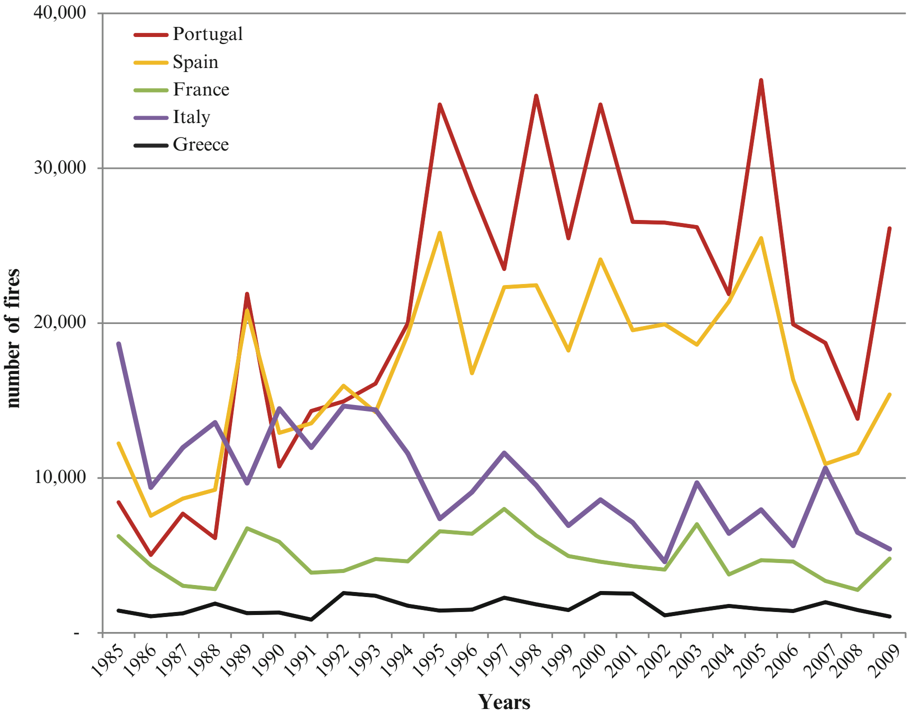

Fig. 2.3 Annual number of fires in the countries of the EUMed region from 1985 until 2009

Table 2.2 Results of the Mann–Kendall test (*S*), associated probabilities (*P*), and Sen slope for the number of fires by country in both periods

Time period	Portugal	Spain	France	Italy	Greece
1985–2009					
S	**110**	82	–28	**–164**	22
P	0.011	0.058	0.528	<0.001	0.623
Sen slope	801.9	396.9	–33.0	–346.2	5.97
2000–2009					
S	**–27**	–21	–7	–7	–17
P	0.020	0.073	0.592	0.592	0.152
Sen slope	–1554.0	–1134.0	–157.5	–201.2	–118.0

Note: Negative values mean a decrease and positive values mean an increase. Significant values are signaled in bold

Both the increasing trend observed for Portugal and the decreasing trend of Italy are significant. In the last decade, a decrease was observed for all the countries, significant only for Portugal, which had a median decrease of over 1,500 fires per year (Sen slope).

In relation to the total burned area, the differences among the countries were also evident (Fig. 2.4). Until the end of the 1990s, Spain usually had the highest burned area, but since 2001 Portugal recorded the highest values, particularly in 2003 and 2005, decreasing considerably afterwards. France and Greece showed, in general, the lowest values of area burned for the whole period, but in Greece the years 2000 and 2007 showed a substantial increase in area burned, in the latter case exceeding all the other countries.

Results of the Mann–Kendall test (Sen 1968) suggests a decreasing trend in all countries during both periods (Table 2.3), with the exception of Greece, where an increasing trend was observed for the last decade. However, a significant trend was observed only for Spain and Italy, which showed a median annual decrease in area burned of 5,175 ha for Spain and 3,243 ha for Italy, for the whole period. The test was not significant for Portugal and France. It must be noted that the Mann–Kendall test, as a non-parametric test, does not consider the absolute change in magnitude from year to year, but just the tendency in a rank ordering of the burnt areas for sequential years.

The average fire size showed a dissimilar spatial trend in relation to the number of fires and burned area, with Greece showing the highest values for nearly all the years, with particular incidence in 2007 (Fig. 2.5). For all the other countries, the average fire size decreased continuously since the 1980s, with annual oscillations more evident in Spain in 1994, in Portugal in 2003 and in Italy in 2007.

2.3.3 Overall Trends by Province (NUTS3)

The overall trend in the number of fires is very irregular depending on the province, although general patterns can be observed by country (Fig. 2.6). Portugal and Spain

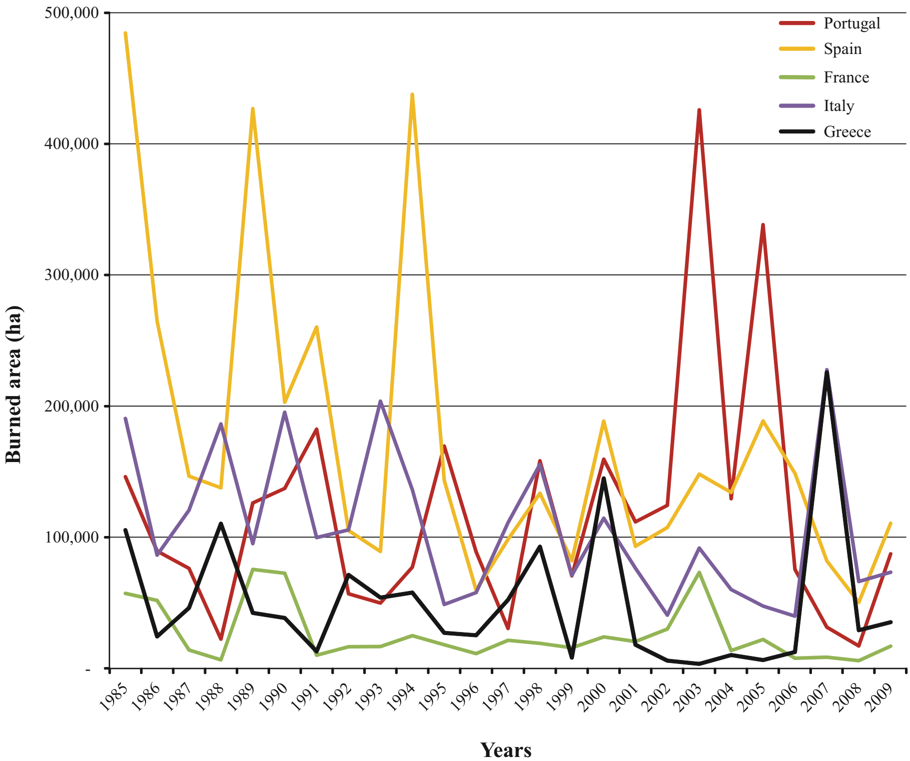

Fig. 2.4 Annual burned area (ha) in the countries of the EUMed region from 1985 until 2009

Table 2.3 Results of the Mann–Kendall test (*S*), associated probabilities (*P*), and Sen slope for the burned area by country in both periods

Time period	Portugal	Spain	France	Italy	Greece
1985–2009					
S	−6	**−100**	−52	**−96**	−68
P	0.907	0.020	0.233	0.026	0.117
Sen slope	−101.6	−5175.0	−473.5	−3243	−1703
2000–2009					
S	−19	−9	−21	−5	11
P	0.107	0.474	0.074	0.720	0.371
Sen slope	−14016.0	−6232.0	−2215.0	−1443.0	2127.0

Note: Negative values mean a decrease and positive values mean an increase. Significant values are signaled in bold

have the majority of provinces with a significant increasing trend, while Italy and Greece have more provinces with a significant decreasing trend. However it should be noted that the Greek data at NUTS3 level after 1998 are incomplete, because of changes in the reporting system in the country. In the case of Italy, an exception

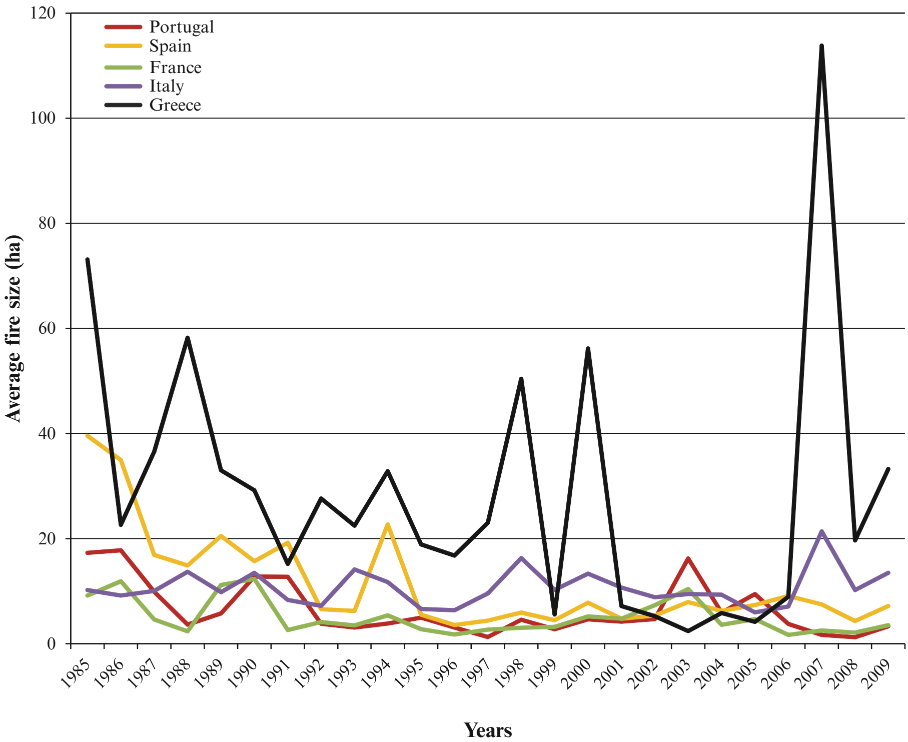

Fig. 2.5 Annual average fire size (ha) in the countries of the EUMed region from 1985 until 2009

occurs in Sicily, where all provinces showed increasing trend or no trend, while in Sardinia almost all the provinces had a decreasing trend. In France, most of the provinces with available data indicated no trend or a decreasing trend. The situation changed when considering only the data between 2000 and 2009. There are just few provinces in the whole study area with a significant trend, either increasing or decreasing, possibly because the time series is too short at this scale of analysis.

The burned area, on the other hand, evidenced a general significant decreasing trend for most provinces both between 1985 and 2009 and in recent years (Fig. 2.7).

2.3.4 Seasonal Trends

Seasonal trends were analyzed at country and regional levels. The average number of fires and average burned area per month between 1985 and 2009 for the EUMed region (Table 2.4) showed that the months with higher number of fires and burned area were August, July and September, respectively. Nearly 73% of the number of

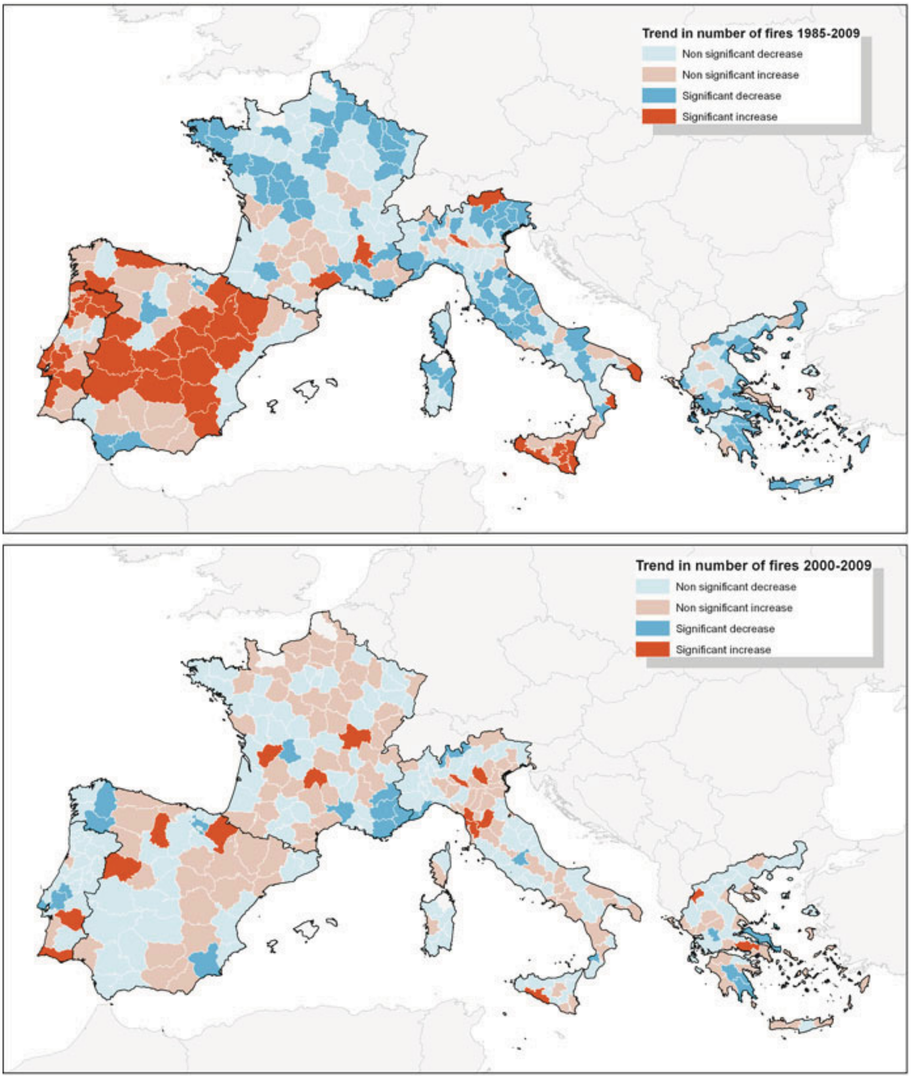

Fig. 2.6 Trend in the number of fires by province in the EUMed region between 1985–2009 (*top*) and between 2000–2009 (*bottom*) obtained with the Mann–Kendall test

fires and nearly 85% of the burned area occurred between June and October. March showed a higher number of fires and burned area in comparison with the other spring months.

At country level, the average trend across months is similar for all countries, even though the absolute number of fires and burned area is highly variable (Figs. 2.8 and 2.9).

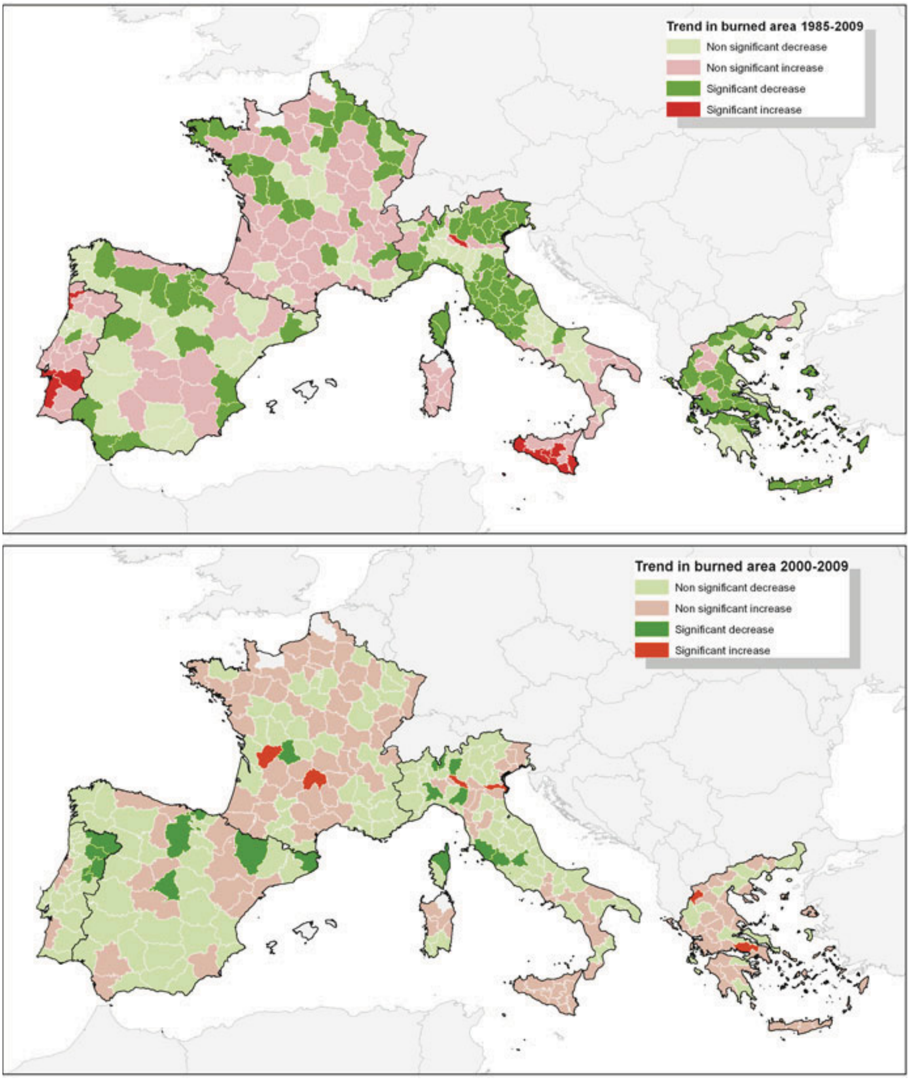

Fig. 2.7 Trend in the burned area (ha) by province in the EUMed region between 1985 and 2009 (*top*) and between 2000 and 2009 (*bottom*), obtained from the Mann–Kendall test

Portugal showed the highest average number of fires between June and November, while in the other months it is surpassed by Spain and in January and February also by Italy. Greece had the lowest average number of fires recorded in the database in all months; however it must be noted that the detailed data by month for the last 2 years is not yet available for this country.

Table 2.4 Annual average (1985–2009) number of fires and burned area per month in the five countries of the EUMed region

Month	Number of fires	% of total number of fires	Burned area (ha)	% of total burned area
January	196	2.0	1,396	1.6
February	484	4.9	2,918	3.3
March	892	9.1	4,730	5.3
April	509	5.2	2,270	2.6
May	318	3.2	1,085	1.2
June	729	7.4	4,307	4.8
July	1,754	17.8	23,198	26.1
August	2,548	25.9	31,451	35.4
September	1,618	16.4	12,790	14.4
October	4,98	5.1	3,055	3.4
November	176	1.8	6,83	0.8
December	134	1.4	1,028	1.2

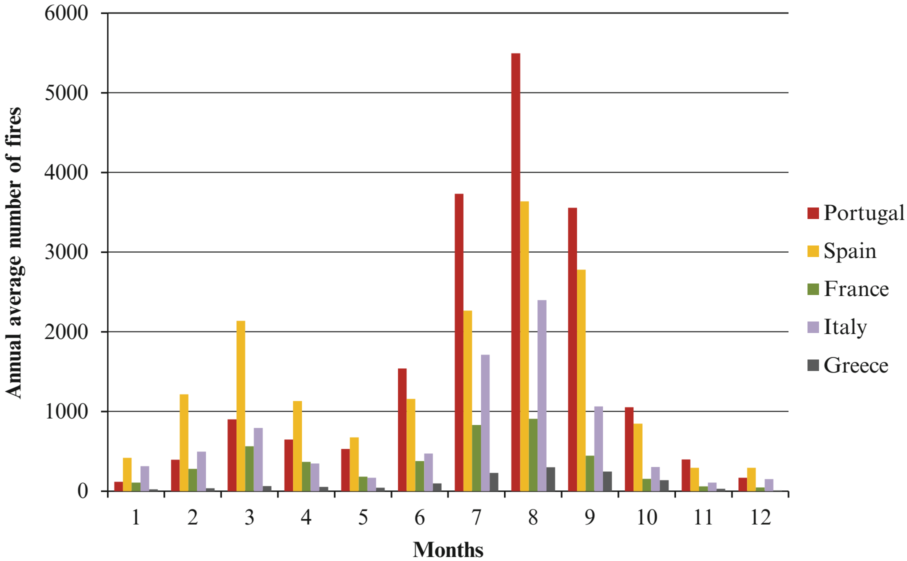

Fig. 2.8 Average number of fires per month in the EUMed countries

The burned area had a different trend; Spain had the highest values for all months, followed by Portugal and Italy. France and Greece showed the lowest values (see Fig. 2.9). Between July and September the average burned area increased substantially in all the countries, reflecting the general weather conditions of this period that promote fire occurrence (hot and dry summer).

Based on these results, the data by country were divided in two different seasons: from June to October, corresponding to the season when most of the fires occur, and

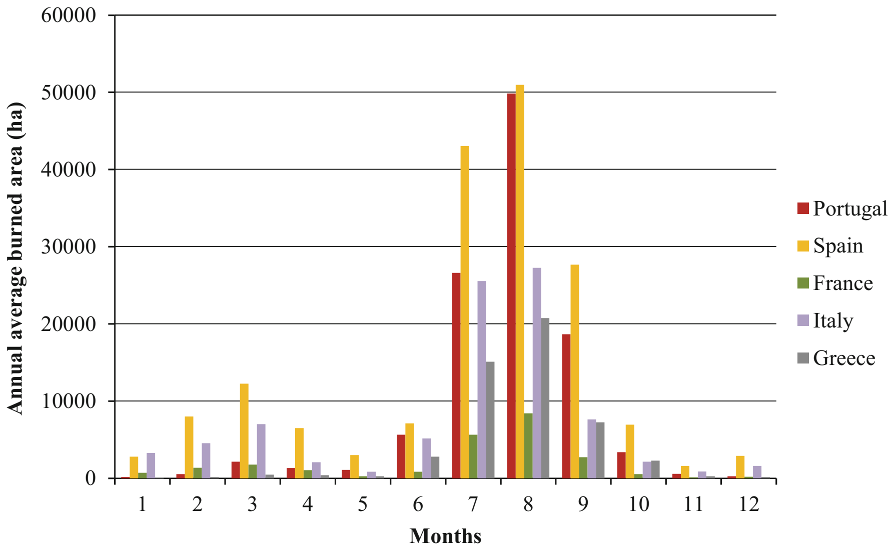

Fig. 2.9 Average burned area (ha) per month in the EUMed countries

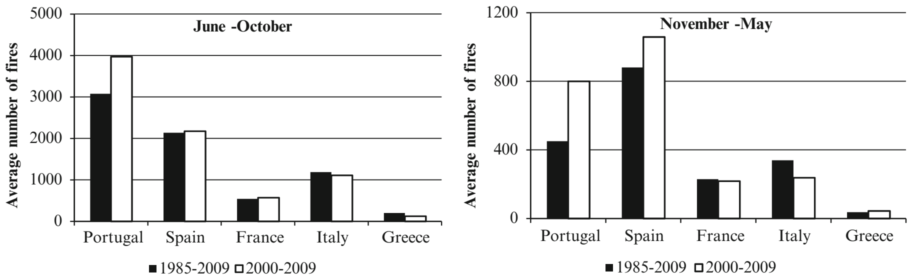

Fig. 2.10 Comparison of the average number of fires for 1985–2009 and 2000–2009 in both seasons

November to May. Comparing the whole time series with the last decade, the average number of fires has increased in both seasons in Portugal and Spain (Fig. 2.10). In Italy it decreased in both periods. In France it increased in June-October but decreased in November-May, whereas the opposite trend was observed in Greece.

In relation to the burned area, Portugal showed an increase in the last decade in both seasons (although no significant trend was found for the overall season in Table 2.3, so this should be interpreted with caution) and Italy a slight increase in the June-October season (Fig. 2.11). In the season November-May, Spain and Italy have the highest average of burned area in both periods, while Portugal is in third position in spite of the observed increase.

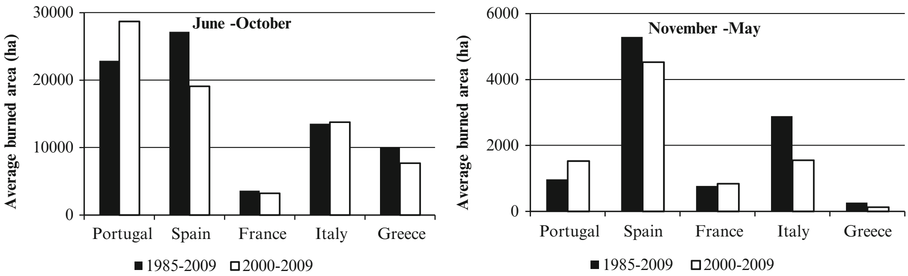

Fig. 2.11 Comparison of the average burned area for 1985–2009 and 2000–2009 in both seasons

2.4 Land Cover Changes in Burned Areas

In this section we aimed to carry out a detailed analysis of land cover changes that occurred in areas affected by fires during the period 2000–2006 in several Southern Europe countries. This was done using the CORINE land cover maps (CLC maps, hereafter) available for 2000 and 2006, and the European Fire Database (EFFIS) containing the annual forest fire information compiled by EU Member States and other European countries (http://effis.jrc.ec.europa.eu). EFFIS database was used for the period 2000–2006. The countries studied included Portugal, Spain, France and Italy. Greece was excluded because the 2006 CLC map was not available for that country.

We worked with the second level of CORINE land cover data and when the results of the analysis indicated the occurrence of a major type of transition at a country level, the third level was used. The areas that were burned in each country and for each year throughout the studied period were obtained after the annual fire maps of the EFFIS database. For each country, a set of seven masks was derived from these fire maps; i.e. one mask for each year from 2000 to 2006. All fires smaller than 50 ha were discarded for the creation of the mask.

Each year the mask was used for extracting two new layers from the two CLC maps of each country. The layer derived from the CLC 2000 map would represent the land cover pre-fire situation in the areas burned that year, whereas the layer derived from the CLC 2006 map would represent the land cover post-fire situation in those same areas. For each year, we combined the two corresponding layers, obtaining a final file in which each polygon would correspond to a given transition of land covers between CLC2000 and CLC2006 and would reflect this information in its attribute table. Based on these data, we generated seven transitional matrices for each country (one per year) and selected, in each case, the major transitional classes to be analyzed at the second CLC data level. An overall transition matrix was also calculated by pooling the data from all countries. Land cover transitions representing less than 50 ha were excluded.

2.4.1 Main Land Cover Types Affected by Wildfires

During the study period (2000–2006), the total burned area in the four considered countries was 1,395,119 ha (only considering fires larger than 50 ha). Half of this area (51%) consisted of CLC Level 2 class 32 (“Scrub and/or herbaceous associations”), followed by class 31 (“Forests”) (34%). At CLC Level 3 fires affected mainly class 324 (“Transitional woodland-scrub”), corresponding to 23% of the total, class 312 (“Coniferous forest”) (15%), followed by classes 311 (“Broad-leaved forest”) (12%) and classes 313 (“Mixed forest”), 321 (“Natural grassland”), 322 (“Moors and heathland”) and 323 (“Sclerophyllous vegetation”), representing each ca. 9% of the total burned area.

2.4.2 Land Cover Changes in Burned Areas

Overall, a total of 1,016,055 ha of burned areas (72.8% of the total) did not change their land cover after fire. The land covers with less persistence in burned areas were Forests, Open spaces with little or no vegetation, and Inland wetlands (Table 2.5). Caution should be taken in interpreting the finding for the latter land cover, as the area with this land cover was very small (150 ha) and thus prone to significant proportional changes even with small variations in polygon boundaries. From the remaining 379,064 ha in which changes occurred, 76.9% became class 32 (“Scrub and/or herbaceous associations”) and 19.6% became class 33 (“Open spaces with little or no vegetation”).

The transition matrix for the overall burned area (Table 2.5) showed that the main changes driven by fire were the transition from forests to open spaces with little or no vegetation (over 50% of the forests in 2000 suffered this transition). The transition from Open spaces with little or no vegetation to Scrub and/or herbaceous vegetation was also relevant (45%), as well as Inland wetlands to Inland waters (46%) Other important transitions were from Arable land to Artificial, non-agricultural vegetated areas (15%). Of these transitions, only the former can be clearly attributed to fire effects.

In Italy, the total area burned during the study period was 79,118 ha (5.7% of the total burned area in the four countries). Fires affected mainly class 211 “Non-irrigated arable land” (22% of the total area burned in the country), class 321 (“Natural grassland”) and class 323 (“Sclerophyllous vegetation”) representing each one ca. 19% of the total area burned, and class 311 (“Broad-leaved forest”) (15%). 68,621 ha of burned areas (86.7% of the total) did not change land cover after fire. From the 10,497 ha that suffered land cover changes, 31% became class 323 (“Sclerophyllous vegetation”), 19% became class 321 (“Natural grassland”), 11% became class 333 (“Sparsely vegetated areas”), 10% became class 243 (“Land principally occupied by agriculture with significant areas of natural vegetation”) and 8% became class 334 (“Burned areas”).

Table 2.5 Transition matrix for the period 2000–2006 in the burned areas in Portugal, Spain, France and Italy

		CLC2006												
		11	12	13	14	21	22	23	24	31	32	33	41	51
CLC2000	11	*1.00*	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	12	0.00	*1.00*	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	13	0.00	0.00	*1.00*	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	14	0.00	0.00	0.00	*1.00*	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	21	0.00	0.00	0.00	**0.15**	*0.82*	0.00	0.00	0.01	0.00	0.01	0.00	0.00	0.00
	22	0.00	0.00	0.00	0.00	0.00	*0.87*	0.01	0.05	0.00	**0.07**	0.01	0.00	0.00
	23	0.00	0.00	0.00	0.00	0.00	0.00	*1.00*	0.00	0.00	0.00	0.00	0.00	0.00
	24	0.00	0.00	0.00	0.00	0.01	0.00	0.00	*0.96*	0.00	0.02	0.01	0.00	0.00
	31	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	*0.41*	**0.51**	**0.07**	0.00	0.00
	32	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	*0.94*	0.05	0.00	0.00
	33	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	**0.45**	*0.54*	0.00	0.00
	41	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	*0.54*	**0.46**
	51	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	*1.00*

Note: Each row provides the proportion of the initial land cover (in 2000) that persisted or changed to other land cover in 2006. Italic cells indicate the persistence values (diagonal) and Bold indicate the main transitions (over 5%). Codes for land cover are: Urban fabric (11); Industrial, commercial and transport units (12); Mine, dump and construction sites (13); Artificial, non-agricultural vegetated areas (14); Arable land (21); Permanent crops (22); Pastures (23); Heterogeneous agricultural areas (24); Forest (31); Scrub and/or herbaceous associations (32); Open spaces with little or no vegetation (33); Inland wetlands (41); Inland waters (51)

In France, the total area burned during the study period was 67.727 ha (4.8% of the total area burned in the four countries). Fires affected mainly classes 323 (“Sclerophyllous vegetation”) and 321 (“Natural grassland”), corresponding to 31% and 17%, respectively, of the total area burned in the country. In addition, fires affected also classes 313 (“Mixed forest”) and 312 (“Coniferous forest”) representing each one ca. 10%. 41,740 ha of the burned areas (61.6% of the total) did not change land cover after fire. From the 25,987 ha that changed land cover trype, 41% became class 334 (“Burned areas”), 30% became class 324 (“Transitional woodland scrub”) and 20% became class 323 (“Sclerophyllous vegetation”).

In Spain, the total area burned during the study period was 492,243 ha (35.3% of the total area burned in the four countries). Fires affected mainly class 324 (“Transitional woodland scrub”), corresponding to 27% of the total area burned in the country, and class 323 (“Sclerophyllous vegetation”) (14%). Classes 321 (“Natural grassland”), 312 (“Coniferous forest”) and 313 (“Mixed forest”) were also strongly subjected to fires (12%, 11% and 10%, respectively, of the total burned area). 381,982 ha of the burned areas (77.6% of the total) did not change land cover after fire, whereas 110,261 ha did. Among the latter, 47% became class 324 (“Transitional woodland scrub”) and 29% became class 334 (“Burned areas”).

In Portugal, the total area burned during the study period was 756,031 ha. This country had, therefore, the largest proportion (54.2%) over the total area burned

Table 2.6 Distribution of the total burned area per country between agradative, degradative and stable land cover transitions

	Italy		France		Spain		Portugal	
	ha	%	ha	%	ha	%	ha	%
Agradative transitions	4,187	5.3	13,331	19.7	36,736	7.5	42,717	5.7
Degradative transitions	6,308	8.0	12,667	18.7	73,524	14.9	243,774	32.2
Stable transitions	68,621	86.7	41,740	61.6	381,982	77.6	469,533	62.1

in the four countries. Fires affected mainly class 324 ("Transitional woodland scrub"), corresponding to 24% of the burned area, class 312 ("Coniferous forest") (19%), class 311 ("Broad-leaved forest") (15%) and class 322 ("Moors and heathland") (11%). 469,533 ha of burned areas (62.1% of the total) did not change land cover after fire, whereas 286,498 ha did, of which 81% became class 324 ("Transitional woodland scrub"), 7% class 334 ("Burned areas") and 3% class 322 ("Moors and heathland").

Classifying all the CLC transition classes into agradative (any transition resulting in an increase of the vegetation cover or leading to a more advanced successional stage), degradative or stable categories, we found clear differences among the considered countries in the distribution of the total burned area among these three types (Table 2.6). In Portugal, Spain and France, the post-fire land cover changes occurred in areas burned between 2000 and 2006 mostly favoured degradative transitions. This degradation trend was particularly strong in Portugal and Spain. In France, agradative transitions represented a slightly larger area than degradative ones.

These results suggest a slow post-fire vegetation dynamics in most of the countries studied. In all of them, except France, degradative transitions accounted for the largest part of the land cover changes that occurred on burned areas. Moreover, a large part of the areas classified as 33 ("Open spaces with little or no vegetation") in CLC 2000 had remained in that same class in CLC 2006, not evolving to classes with increased vegetation cover or towards more mature successional stages. This slow dynamics may be due to various factors. First of all, in Spain and Portugal (the two countries with the smallest proportion of agradative transitions), more adverse climatic conditions (i.e. dryer conditions) in many of the areas affected by fires may have caused lower rates of post-fire vegetation recovery. Secondly, in those two countries, a large part of the fires occurred in the last 2 years of the studied period (2005 and 2006). In Spain and Portugal, these fires accounted for 38% and 33%, respectively, of the total burned area in each case, whereas in Italy and France, these values were much lower (26% and 11%, respectively). In the two former countries, thus, a larger extent of burned areas had a very short time to recover, which, obviously, influenced the results.

In general, the length of the study period was short, as the maximum post-fire period that could be monitored was 6 years. We have to highlight, therefore, that in most cases our results are documenting post-fire land cover dynamics on the short (or sometimes medium) term.

2.5 Fire Effects on Land Cover Change Dynamics in the Period 2000–2006

In this section our aim was to evaluate the role of fire in the observed landscape dynamics at European level. The land cover dynamics analysis consisted in the comparison of the observed land cover change and transitions in burned and unburned areas. This analysis was carried out using CORINE Land Cover (CLC) data for 2000 and 2006 and the fire perimeters for fires larger than 500 ha obtained from the EFFIS database.

The results obtained for land cover dynamics analysis are presented in this section as transition matrices. For each of a total of 702 fire perimeters, we considered a paired unburned area with a similar shape, and surrounding the burned patch. To characterize land cover change, the thematic legend (third level) of the CLC layer has been aggregated into a new one composed by six main categories (urban, artificial, agricultural, forest, shrubland and no vegetation areas) in order to simplify the land cover dynamics analysis. This has been done both for CLC 2000 and 2006, and as result two new land use layers were obtained. A transition matrix was computed separately for each burned – unburned patch pair. The differences between these two matrices were then summarized in a new matrix called change-intensity matrix which represented the rates of land cover change in burned versus unburned areas.

In unburned areas (Table 2.7), persistence of the land covers (diagonal values of the matrix) were always larger than 90% with the exception of forests and areas with no vegetation, where it decreased to ca. 70%. The main transitions were from forests to shrublands (26%) and no vegetation to shrublands (30%). The latter transition seems to reflect the process of secondary succession and scrub encroachment, probably in former burned areas, sparsely vegetation areas or even bare ground. The former is probably a consequence of forest logging. In burned areas, the persistence pattern of the different land cover types was similar to the one of unburned areas: also always larger than 90% with the exception of forests and areas with no vegetation, but is this case it was even lower, ca. 35–50% (Table 2.7). Here the main transitions were also from forests to shrublands (57%) but also to areas with no vegetation (6%), from areas with no vegetation to shrublands (49%), and, to a lesser extent, from shrublands to areas with no vegetation (6%). The transition of forests to shrublands and areas with no vegetation could be explained mainly by wildfires. After fires, in a period of 6 years (from 2000 to 2006) areas may not be able to have a significant vegetation development, or only shrublands are able to grow in the early stages of succession. Even if there is forest recovery it will be in an earlier stage of development and would have a shrubland-like physiognomy, or would consist of a transition category between forest and shrub which in this work is categorized as shrubland (see proposed legend). The same driver (fire) can explain the transition from shrublands to areas with no vegetation. In contrast, the significant transition from areas with no vegetation to shrublands may be an evidence of post-fire vegetation recovery, mainly in situations where the areas were burned in the beginning of the study period (2000). It must be taken into account that this land cover class

Table 2.7 Transition matrices (expressed as percentages) for burned and unburned areas in the 2000–2006 period

Difference

	To 2006	Urban	Artificial	Agricultural	Forest	Shrubland	No vegetation
From 2000	Urban	−0.5	0.0	−0.1	−0.2	0.7	0.0
	Artificial	−0.7	−1.2	0.7	0.9	0.0	0.3
	Agricultural	−0.8	0.0	−0.9	−0.3	1.4	0.6
	Forest	−0.1	−0.1	−0.2	−35.3	30.7	4.9
	Shrubland	0.0	−0.1	−0.3	−3.6	0.9	3.2
	No vegetation	0.0	−0.8	−0.8	−0.1	18.7	−17.1

Burned

	To 2006	Urban	Artificial	Agricultural	Forest	Shrubland	No vegetation
From 2000	Urban	98.5	0.0	0.6	0.0	0.9	0.0
	Artificial	0.1	96.2	1.1	1.3	0.8	0.5
	Agricultural	0.2	0.1	95.2	0.3	3.5	0.7
	Forest	0.0	0.1	0.4	36.3	57.1	6.2
	Shrubland	0.0	0.1	0.9	1.1	92.3	5.6
	No vegetation	0.0	0.3	0.3	0.2	48.6	50.6

Unburned

	To 2006	Urban	Artificial	Agricultural	Forest	Shrubland	No vegetation
From 2000	Urban	99.0	0.0	0.6	0.2	0.2	0.0
	Artificial	0.8	97.4	0.4	0.4	0.7	0.2
	Agricultural	1.0	0.1	96.1	0.6	2.0	0.2
	Forest	0.1	0.2	0.6	71.6	26.4	1.2
	Shrubland	0.0	0.2	1.2	4.7	91.4	2.4
	No vegetation	0.0	1.1	1.1	0.3	30.0	67.6

Note: Each value in the matrices represents the average value for a sample of 702 wildfires and respective unburned pairs, and each row represents the proportion of the land cover in 2000 that was kept or changed in 2006. The change intensity matrix (Difference matrix, on the top) represents the difference between burned (middle) and unburned (bottom) areas matrices includes also burned areas and sparsely vegetated areas, thus the succession to shrubland-type vegetation is a possible explanation. Alternatively, misclassification of the land cover types in the two different time periods could explain this result, if many areas with no vegetation in 2000 had been classified as shrublands in 2006 (but if that is the case this mistake must have been made also in unburned areas).

The intensity change matrix shows that wildfires have caused changes in land cover dynamics (Table 2.7). In terms of persistence, fire decreased the persistence for all land cover types except shrublands. So, fire promoted faster land cover changes.

The more notorious decrease in persistence was for forests and areas with no vegetation. It is logical that forests are the land cover more easily changed by fire, and thus less persistent. The trend for areas with no vegetation might again be explained by different criteria in classifying the same land cover in the two time periods. The major land cover transitions promoted by fire were the forest to both shrubland cover (+30%) and to areas with no vegetation (+5%). So, as expected, fire causes a much faster change from forests to areas with shrublands or no vegetation in the short term, compared to unburned areas. A similar trend was observed by for specific regions of Portugal and Spain (Lloret et al. 2002; Viedma et al. 2006; Silva et al. 2011). The other significant transition was from shrublands to areas with no vegetation (+19%), although this could be interpreted as a simple maintenance of the same land cover in case the hypothesis of misclassification is confirmed. Other land cover transitions favored by fire included shrublands to no vegetation (+3%) and agricultural areas to shrublands (+1.5%), the latter either reflecting a trend for the abandonment of agriculture in burned areas, as hypothesized by Silva et al. (2011) for three regions in Portugal, or the assignment of different categories to the same land cover (e.g. pastures versus natural grasslands).

Land cover transitions promoted by the absence of fire were less notorious. Larger differences were registered for the transition from shrublands to forest (−4%), reflecting secondary succession in the vegetation, from areas with no vegetation to artificial and agricultural areas (−0.8%), and from agricultural to urban areas (−0.8%). The latter transitions suggest that urbanization processes are more common in unburned areas, compared to the burned ones.

2.6 Key Messages

- Land cover changes in Southern Europe in the period 1990–2006 suggest a decrease in fire hazard in this region, as landscape changes corresponding to increased fire hazard occur in a smaller geographic area (4.9 million hectares) than transitions corresponding to decreased fire hazard (5.4 million hectares). This might be explained by disturbances such as logging, drought, wildfires, as well as urbanization;
- Compared with the overall period 1985–2009, changes in the fire regime have been observed in the last 10 years (2000–2009) in Southern Europe. The long-term

trend for the number of fires was an increase, but in the last 10 years the trend was the opposite, a high decrease. In relation to the total burned area, the general trend is for a decrease, lower when considering the entire time series and more pronounced in the last 10 years. For the period 1980–2009, the provinces with a high increase in both number of fires and burned area, were located in Portugal, Central Spain, Southern Sicily and Southeast France. The decreasing trends were found mostly in the Northern provinces of Spain and in Central Greece. The majority of the provinces of Italy and Greece showed no trend. For the period 2000–2008, the majority of provinces in all the countries show a decreasing trend, with a few exceptions in France and Italy;

- The average number of fires has substantially increased in Portugal and Spain in both the "fire season" (June to October) and the rest of the year, while for the other countries the trend is more constant;
- In the period 2000–2006, fires burned mainly areas of forest and shrublands. The main CORINE land cover categories affected were "Transitional woodland-scrub" (23% of the total burned areas, "Coniferous forest" (15%), followed by "Broad-leaved forest", "Mixed forest", "Natural grassland", "Moors and heathland" and "Sclerophyllous vegetation" (ca. 10% each). Almost 97% of the areas burned during 2000–2006 changed their land cover to "Scrub and/or herbaceous associations" or "Open spaces with little or no vegetation";
- Wildfires affected landscape change dynamics. Fire decreased the persistence for all land cover types except shrublands. The major land cover transitions promoted by fire were the forest to both shrublands (+30%) and to areas with no vegetation (+5%). The other significant transition was from shrublands to areas with no vegetation (+19%), although this could be interpreted as a simple maintenance of the same land cover that was classified differently. Land cover transitions promoted by the absence of fire were less obvious. Larger differences were registered for the transition from shrublands to forest (−4%), reflecting secondary succession in the vegetation.

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APPENDIX D. MODELADO DE LA VARIACIÓN ESPACIAL DE LOS FACTORES EXPLICATIVOS DE LA CAUSALIDAD HUMANA EN INCENDIOS FORESTALES MEDIANTE REGRESIÓN LOGÍSTICA PONDERADA GEOGRÁFICAMENTE

This appendix introduces the first steps in estimating the spatial variation of the explanatory factors of human causality.

Modelado de la variación espacial de los factores explicativos de la causalidad humana en incendios forestales mediante Regresión Logística Ponderada Geográficamente

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RESUMEN

Este trabajo tiene como objetivo el análisis de la variación espacial de los factores explicativos de la causalidad humana en los incendios forestales en la España continental, utilizando técnicas de Regresión Logística dentro del contexto de los modelos de Regresión Ponderada Geográficamente. Para ello se ha realizado el análisis estadístico y la modelización espacial en entorno SIG, tanto de la ocurrencia histórica como de los principales factores explicativos. Los resultados indican que los valores más elevados de probabilidad de ocurrencia ligados a causalidad humana se asocian a zonas de interfase cultivo-forestal, especialmente en el sector noroeste y en los bordes de las zonas montañosas, y a zonas de interfase urbano-forestal, de gran importancia en la zona centro y el litoral mediterráneo. Estas dos variables son las de mayor carga explicativa en el modelo atendiendo a valores de t de Student, siendo significativas al 95%, llegando en algunas zonas a más del 99%. La cartografía evidencia además el carácter explicativo de algunas variables de implantación lineal como tendidos eléctricos, líneas de ferrocarril o pistas forestales. El grado de ajuste del modelo, calculado mediante R^2 local de la muestra de calibración, se sitúa en un valor promedio de 0,7. El porcentaje de acierto en la clasificación de la ocurrencia es de 87% y 76%, con un acuerdo de 0,73 y 0,52 según la Kappa de Cohen, para los periodos 1988-2007 y 2008-2011 respectivamente.

PALABRAS CLAVE

Riesgo de incendio, causalidad humana, incendios forestales, GWR, modelado SIG.

ABSTRACT

This work aimed to analyze the spatial variation in the explanatory factors of human-caused wildfires in the continental Spain using Logistic Regression techniques within the framework of Geographically Weighted Regression models. To this end, statistical analysis and spatial modeling in GIS environment of the historical occurrence and the main explanatory factors was carried out. Results suggest that high fire risk rates are related to Wildland-Agricultural interface, especially in the northwest and along the edges of the mountainous areas, and to Wildland-Urban interface, mainly in the central Spain and the Mediterranean coast. These two variables are the most explanatory burden on the model response to Student's t values, being significant at $p<0.05$, reaching in some areas over $p<0.01$. The mapping also evidences the importance of the explanatory variables with linear deployment as power lines, railroads or trails. The degree of fit, calculated using local R^2 with the calibration sample, is at an average value of 0.7. The percentage of accurate classification of occurrence is 87% and 76%, with an *agreement of 0.73 and 0.52 by Cohen's kappa for the validation periods 1988-2007 and 2008-2011 respectively.*

KEY WORDS

Fire risk, human causality, forest fires, GWR, GIS modeling.

1 INTRODUCCIÓN

Los incendios forestales juegan un papel crítico en la transformación del paisaje, la sucesión de la vegetación, la degradación del suelo y la calidad del aire. Aunque el fuego ha sido utilizado históricamente como una herramienta para la gestión del uso del suelo y muchos ecosistemas están bien adaptados a los ciclos de incendios, los cambios recientes en cuanto al clima y los factores sociales relacionados con el fuego pueden transformar los regímenes tradicionales de incendio, incrementando sus efectos negativos. En este sentido, el papel del cambio climático en el aumento de la frecuencia de los incendios y la intensidad del fuego se ha documentado en varios ecosistemas (Kasischke y Turetsky, 2006; Westerling *et al*., 2006). Las actuales proyecciones climáticas apuntan hacia peores condiciones en las próximas décadas para la mayoría de las regiones tropicales y boreales (Flannigan *et al*., 2005). Además de los efectos globales, los incendios tienen efectos locales también importantes, comúnmente asociados a frecuencia e intensidad del fuego, lo que implica degradación y erosión del suelo, pérdida de vidas y biodiversidad y daños en propiedades e infraestructuras (Omi, 2005).

Por otro lado, la dinámica de los regímenes de incendios en el sur de Europa se relaciona principalmente con factores humanos. De hecho, la causalidad humana es responsable de más del 95% de los incendios que tienen lugar en esta región (San-Miguel y Camiá, 2009), si bien existen variaciones espaciales en su contribución al total de la ocurrencia. En este contexto, las mejoras e innovaciones en la estimación del riesgo de incendio son de vital importancia para reducir los impactos negativos, por cuanto además de facilitar la prevención ayudan a dirigir actuaciones tendentes a disminuir la gravedad o intensidad de la quema a través de la gestión del combustible, u orientar los tratamientos post-incendio. Además, la determinación de los factores causales facilita la proyección a escenarios de riesgo futuro en condiciones climáticas de cambio. A pesar de la importancia de los aspectos humanos en la ocurrencia, poco trabajo se ha dedicado a este tema, tal vez debido a la complejidad de predecir el comportamiento humano, tanto en el espacio como en el tiempo.

Por otra parte, el ajuste de modelos estadísticos de estimación del riesgo, previamente abordados para diferentes regiones dentro de la Península Ibérica (Chuvieco *et al*., 2010), ha puesto en evidencia que los factores explicativos también varían espacialmente en su significación y contribución. Como consecuencia, la utilización de métodos globales de regresión para territorios extensos y variados, como el ahora analizado, resulta inadecuada al aplicar coeficientes constantes. Para superar esta limitación, en el presente trabajo se han utilizado técnicas de regresión ponderada geográficamente (GWR, *Geographically Weighted Regression*) (Fotheringham *et al*., 2002), que permiten incorporar en los modelos la variación espacial de la carga explicativa de las variables predictivas. Se pueden encontrar ejemplos de uso de GWR aplicada a diversos campos de estudio en Li *et al*. (2010), Lu *et al*. (2011), Tu (2011), Cardozo *et al*. (2012) o Su *et al.* (2012), y aplicada concretamente a la ocurrencia de incendios forestales en Koutsias *et al*. (2005) y Martínez y Koutsias (2011).

En este contexto se ha aplicado la Regresión Logística (LR, *Logistic Regression*) binaria, comúnmente utilizada para la explicación probabilística de la ocurrencia de causa humana (Martínez *et al*., 2004; Vasconcelos *et al*., 2001; Vega-García *et al*., 1995; Chuvieco *et al*., 2010). El ajuste del modelo GWLR (*Geographically Weighted Logistic Regression*) ha requerido el análisis estadístico y espacialización tanto de la ocurrencia histórica 1988-2007 como de una amplia cantidad de variables explicativas, seleccionadas a partir de la experiencia previa en modelos regionales y nacionales (Vilar *et al*., 2008; Martínez *et al*., 2009; Chuvieco *et al*., 2010). Dicho ajuste se ha llevado a cabo utilizando una muestra aleatoria del 60%, reservando el 40% restante para el proceso de validación. Asimismo, se ha utilizado una segunda muestra de validación confeccionada a partir de la ocurrencia registrada durante el periodo 2008-2011. El objetivo de este trabajo es, por tanto, la modelización y análisis de la variación en el territorio de los factores antrópicos ligados a la ocurrencia de incendios forestales mediante el uso de técnicas GWLR. Este trabajo se ha desarrollado en el marco del proyecto FIREGLOBE (www.fireglobe.es, Chuvieco *et al*., 2011).

En los siguientes apartados se detalla el método seguido para la modelización de la variación espacial de los factores explicativos. A continuación se presentan los principales resultados obtenidos. Seguidamente se muestra el grado de ajuste del modelo así como los resultados del proceso de validación. Finalmente se presenta por una parte la comparación de los resultados obtenidos con algunos estudios previos así como las principales conclusiones y el trabajo futuro a desarrollar.

2 METODOLOGÍA

La metodología para el modelado de la causalidad humana en incendios forestales se basa en el uso de técnicas de GWLR. Al igual que los modelos de Regresión Logística Global (GLR, *Global Logistic Regression*), los modelos GWLR son de naturaleza estadística y permiten conocer la relación entre una variable dependiente cualitativa, dicotómica en nuestro caso, y una o más variables explicativas independientes, o covariables, ya sean cualitativas o cuantitativas. Por lo tanto, para su desarrollo se requiere por una parte una variable dependiente binaria, en este caso la alta/baja ocurrencia de incendios, y por otra una serie de variables explicativas que se enumerarán más adelante. En la figura 1 se muestra un esquema del flujo de trabajo seguido para la modelización de la causalidad humana.

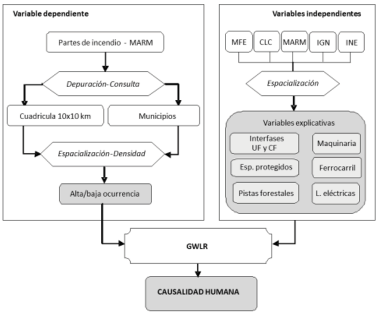

Figura 1. Flujo de trabajo para el modelado de la causalidad humana en incendios forestales.

2.1 Variable dependiente

La variable dependiente binaria –alta/baja ocurrencia de incendios– está construida a partir de la base de datos de incendios en España en el periodo 1988-2007 (MARM), utilizando para su espacialización la retícula de 10x10 km utilizada por los servicios de extinción para la localización parcial de los fuegos y la cartografía digital de municipios en España. De este modo, tras la depuración de la base de datos, se han seleccionado y espacializado los incendios de causa humana de más de 1 ha a través de la asignación aleatoria de cada uno de ellos a su respectiva combinación de cuadrícula /municipio, acotado además a la zona forestal (de la Riva *et al*., 2004; Amatulli *et al*., 2007). Esto permite el cálculo de mapas de densidad de incendios con resolución de 1x1 km. Estos valores de densidad se han dicotomizado en alta (1) y baja ocurrencia (0) mediante la separación de la muestra en terciles, considerando alta ocurrencia el tercer tercil (muestra por encima del percentil 66 –1,83 incendios/km^2–) y baja ocurrencia el primer tercil (muestra por debajo del percentil 33 –1,00 incendio/km^2–), descartándose del análisis el segundo tercil.

2.2 Variables independientes

Como ya se ha dicho anteriormente, las variables explicativas han sido seleccionadas a partir de la experiencia previa en modelos regionales y nacionales (Vilar *et al*., 2008; Martínez *et al*., 2009; Chuvieco *et al*., 2010). Las variables explicativas consideradas son:

- Interfases. Superficie ocupada por el *buffer* de 200 metros desde la línea de contacto hacia la zona forestal:
  - Interfase urbano-forestal (ICF), derivada del Mapa Forestal de España 1:200000 (MFE200).
  - Interfase cultivo-forestal (IUF), obtenida del MFE200.
  - Interfase pasto-forestal (IPF), derivada del MFE200.
- Montes de Utilidad Pública. Delimitación de la superficie ocupada por montes incluidos en el catálogo de Utilidad Pública.
- Espacios protegidos. Delimitación de la superficie ocupada por espacios naturales protegidos (ENP) y Red Natura 2000.
- Variación en el potencial demográfico 1991-2006 (Calvo y Pueyo, 2008).
- Cambios en la ocupación del suelo. Pérdida o ganancia de superficie ocupada por suelo forestal.
- Líneas eléctricas. Superficie ocupada por el buffer de 50 metros a cada lado de la red de transporte de alta, media y baja tensión, obtenida de la Base Cartográfica Numérica 1:200000 (BCN200).
- Líneas de ferrocarril. Superficie ocupada por el buffer de 200 metros a cada lado de la red de ferrocarril (excluyendo la red de alta velocidad), obtenida de la BCN200.

- Pistas forestales. Superficie ocupada por el buffer de 200 metros a cada lado de la red de pistas forestales, obtenida de la BCN200.
- Tasa de paro. Obtenida, por municipios para 2007, del Censo de Población y Viviendas 2001 (resultados actualizados para 2007) del Instituto Nacional de Estadística (INE).
- Porcentaje de jefes de explotación mayores de 55 años. Obtenido a nivel municipal del Censo Agrario de 1999 del INE.
- Ganado no estabulado. Número de cabezas de bovino a nivel municipal, obtenido del Censo Agrario de 1999 del INE.
- Ocupados en el sector primario. Obtenido por municipios del Censo Agrario de 1999 del INE.
- Densidad de maquinaria agrícola. Calculada como el cociente entre el total de maquinaria agrícola disponible (obtenido del Censo Agrario de 1999 del INE) y la superficie municipal.

Todas estas variables han sido espacializadas con una resolución de celda de 1x1 km, al igual que la variable dependiente (figura 2). Para asegurar la consistencia de los resultados se ha llevado a cabo el análisis de colinealidad de las variables explicativas.

Para determinar la variables que finalmente serían incluidas en el modelo, se ha ajustado un modelo GWLR incluyendo la totalidad de las variables consideradas, descartando del modelo final las que, o bien no han resultado significativas según el valor de *t de Student* ($p<0,05$), o el sentido explicativo obtenido según el modelo no era coherente con lo que cabría esperar en función de la experiencia previa y la opinión de expertos. Las variables utilizadas para el ajuste del modelo definitivo son: Interfase Cultivo-Forestal, Interfase Urbano-Forestal, Espacios Naturales Protegidos, Líneas Eléctricas, Pistas Forestales, Líneas de Ferrocarril y Densidad de Maquinaria Agrícola.

2.3 GWLR

Las técnicas GWR extienden el uso tradicional de los modelos de regresión globales permitiendo el cálculo de parámetros de regresión locales. Tomando como punto de partida la ecuación típica de la regresión logística:

$$y_i = \frac{e^{(\beta_0+\beta_1 x_{1i}+\ldots+\beta_k x_{ki})}}{1+e^{(\beta_0+\beta_1 x_{1i}+\ldots+\beta_k x_{ki})}} \qquad (1)$$

la expresión matemática de su versión geográficamente ponderada es:

$$y_i = \frac{e^{(\beta_0(u_i,v_i)+\beta_1(u_i,v_i)x_{1i}+\ldots+\beta_k(u_{ki},v_{ki})x_{ki})}}{1+e^{(\beta_0(u_i,v_i)+\beta_1(u_i,v_i)x_{1i}+\ldots+\beta_k(u_{ki},v_{ki})x_{ki})}} \qquad (2)$$

siendo (*ui,vi*) las coordenadas de localización en el espacio del punto *i*.

De acuerdo con esto, la utilización de modelos GWLR permite obtener coeficientes de regresión cuyo valor varía espacialmente, obteniendo así un conjunto de coeficientes distinto para cada una de las localizaciones que conforman la muestra de análisis. Para ello, se ajusta un modelo de regresión para cada punto, considerando en el proceso la influencia de sus vecinos más próximos, a los que se les asigna un peso inversamente proporcional al cuadrado de la distancia (Fotheringham *et al*., 2002). El umbral de distancia se puede establecer –optimizar– mediante la minimización del cuadrado de los residuales (*Cross-Validation*, Cleveland, 1979) o mediante la minimización del *Akaike Information Criterion* (adaptado a GWR según Hurvich *et al*., 1998).

Además de los coeficientes de regresión, el modelo GWLR permite calcular una serie de parámetros estadísticos útiles como el valor de la *t de Student* de cada una de las variables explicativas (utilizado para determinar su nivel de significancia) y el valor del R^2 local (es decir, el valor del R^2 del modelo resultante en el punto al que se refiere el valor y sus vecinos), entre otros.

No obstante, la GWLR no permite la estimación de los coeficientes de regresión en localizaciones en las que no se tiene observación. Con el fin de superar esta limitación y poder aplicar el modelo a la totalidad de la superficie del área de estudio, los coeficientes de regresión han sido interpolados utilizando métodos locales conservando así los valores originales de las localizaciones con observación y, por lo tanto, la consistencia interna del modelo.

En este trabajo el ajuste del modelo GWLR se ha llevado a cabo utilizando una muestra aleatoria del 60% de la muestra total, reservando el 40% restante para el proceso de validación. La calibración del modelo se ha llevado a cabo utilizando *Adaptive Kernel* para la selección del número de vecinos, optimizado mediante *Cross-Validation*. El número de vecinos considerados es de 914.

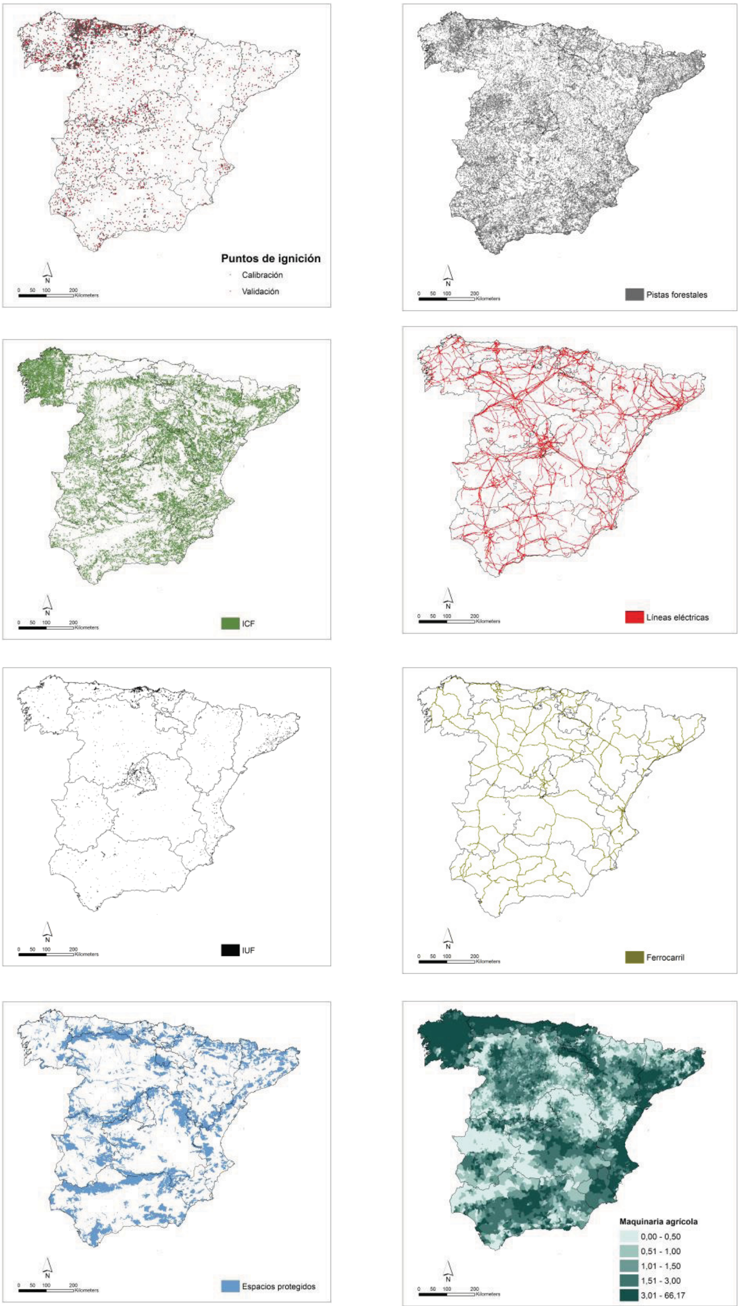

Figura 2. Variables consideradas en el modelo GWLR.

2.4 Ajuste y validación

El proceso de validación se ha llevado a cabo utilizando los valores de R^2 local obtenidos durante la calibración del modelo y que permiten realizar una primera valoración del grado de ajuste del modelo. Por otra parte, se ha llevado a cabo la clasificación del porcentaje de acierto y el cálculo del grado de acuerdo según el valor de la *Kappa de Cohen*. Para ello se ha utilizado, por una parte, el 40% reservado de la muestra 1988-2007 y, por otra, una segunda muestra de validación construida a partir de los incendios registrados durante el periodo 2008-2011. Estos últimos se han espacializado siguiendo el mismo proceso y los mismos umbrales para su clasificación en alta y baja ocurrencia que los aplicados para el periodo 1988-2007. La motivación para utilizar dos muestras de validación tomando sendos periodos es la de testar en la medida de lo posible el carácter prospectivo del método propuesto a través de la clasificación de la ocurrencia en un periodo distinto (2008-2011) al utilizado para la calibración del modelo (1988-2007).

3 RESULTADOS

Los principales resultados obtenidos en la modelización de la causalidad humana en incendios forestales son: los coeficientes de regresión de las variables explicativas, la variación espacial en la significación de dichas variables y la probabilidad de ocurrencia de incendio relacionada con la causalidad humana.

En la figura 3 se presenta la cartografía de los coeficientes de regresión interpolados asociados a las variables predictivas. Como se puede observar, los valores de estos coeficientes varían espacialmente como resultado del ajuste mediante GWLR. En este punto, debe resaltarse que estos valores no están directamente relacionados con un mayor o menor peso en el modelo, sino con las unidades de medida de las variables predictivas. Para conocer el grado de participación de las variables en la modelización deben tomarse como referencia los umbrales de significación, cartografiados en la figura 4. Dichos umbrales, además de guardar relación con el grado de participación de las distintas variables en el modelo, también aportan información acerca del sentido explicativo que juega cada una de ellas. De este modo, a mayor umbral de significación y, por tanto, mayor valor de la *t de Student* (con independencia de su signo), mayor es el peso de la variable en el modelo. Por otro lado, valores positivos en el umbral de significación conllevan una relación directa entre la variable explicativa en cuestión y la causalidad humana o, lo que es lo mismo, cuanto mayor es el valor de la variable predictiva mayor es la probabilidad de ocurrencia, y viceversa. En el caso contrario, es decir, valores de *t de Student* por debajo de 0, encontramos una relación inversa entre los valores de las variables explicativas y la ocurrencia, siendo menor la probabilidad de ocurrencia cuanto mayor es el valor de la variable. Para una correcta interpretación de estos resultados es importante resaltar en este punto el hecho de que la cartografía de umbrales de significación representa en cada uno de los puntos un valor obtenido del modelo calibrado localmente con una muestra compuesta por el punto en cuestión y los 914 vecinos más próximos, y no únicamente el valor obtenido en el punto representado.

Un análisis más detallado de la cartografía de umbrales de significación permite observar que la mayor carga explicativa recae sobre la variable ICF. Contrariamente a lo que sucede con el resto de variables, que no superan el umbral de $p<0,25$ en algunos puntos del territorio, la ICF aparece como significativa con $p<0,05$ en prácticamente la totalidad de las localizaciones. A esto hay que sumarle el hecho de que el sentido explicativo de la ICF en la causalidad humana es siempre positivo. Reseñable es también la contribución a la explicación de la causalidad de la IUF, que juega un papel importante en las localizaciones situadas en el triángulo imaginario formado por la zona central de la península (Comunidad de Madrid) y la costa mediterránea (especialmente el tramo Valencia-Barcelona). A continuación, ordenadas según su umbral de significación máximo aparecen las variables correspondientes a infraestructuras de implantación lineal: líneas de ferrocarril, tendidos eléctricos y pistas forestales. Las líneas de ferrocarril, al igual que la ICF, presentan un sentido explicativo positivo en todas sus localizaciones. En el caso de los tendidos eléctricos y las pistas forestales, si bien la mayor parte de sus localizaciones significativas con $p<0,25$ tienen sentido explicativo positivo, existen algunos puntos con sentido negativo, si bien su umbral de significación es bastante bajo ($p<0,25$). Lo mismo sucede en el caso de la densidad de maquinaria agrícola, cuyo sentido explicativo se esperaría positivo en todas las localizaciones de la muestra, y aparece con signo negativo en la zona correspondiente a la Cornisa Cantábrica y Galicia. No obstante, este hecho puede ser debido en parte a que esta variable es de tipo estadístico y su valor se asigna a todas la superficie municipal, lo que ligado a la alta ocurrencia registrada en esas zonas puede llevar a esta situación. Por último, la variable espacios protegidos interviene en el modelo como agente disuasorio o atenuante de la causalidad humana en la mayor parte del territorio, apareciendo con sentido positivo tan solo en algunas localizaciones del noroeste peninsular.

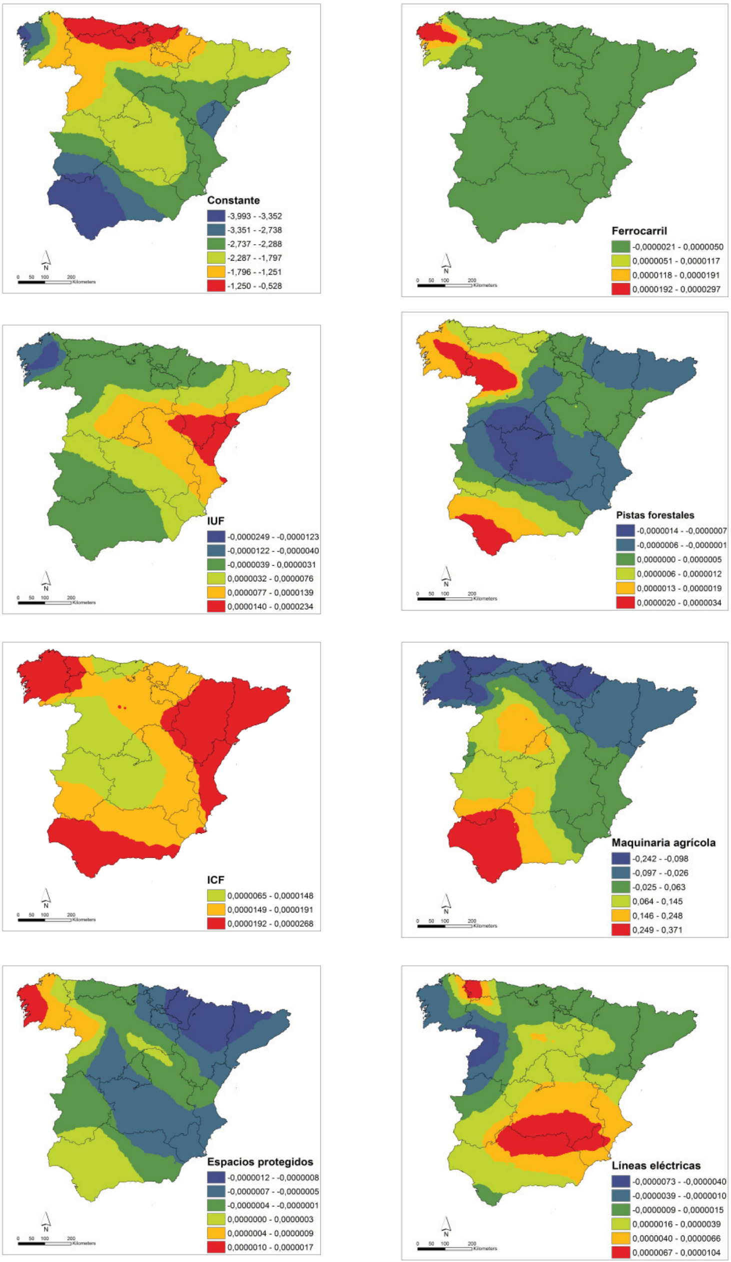

Figura 3. Coeficientes de regresión de las variables explicativas en el modelo GWLR.

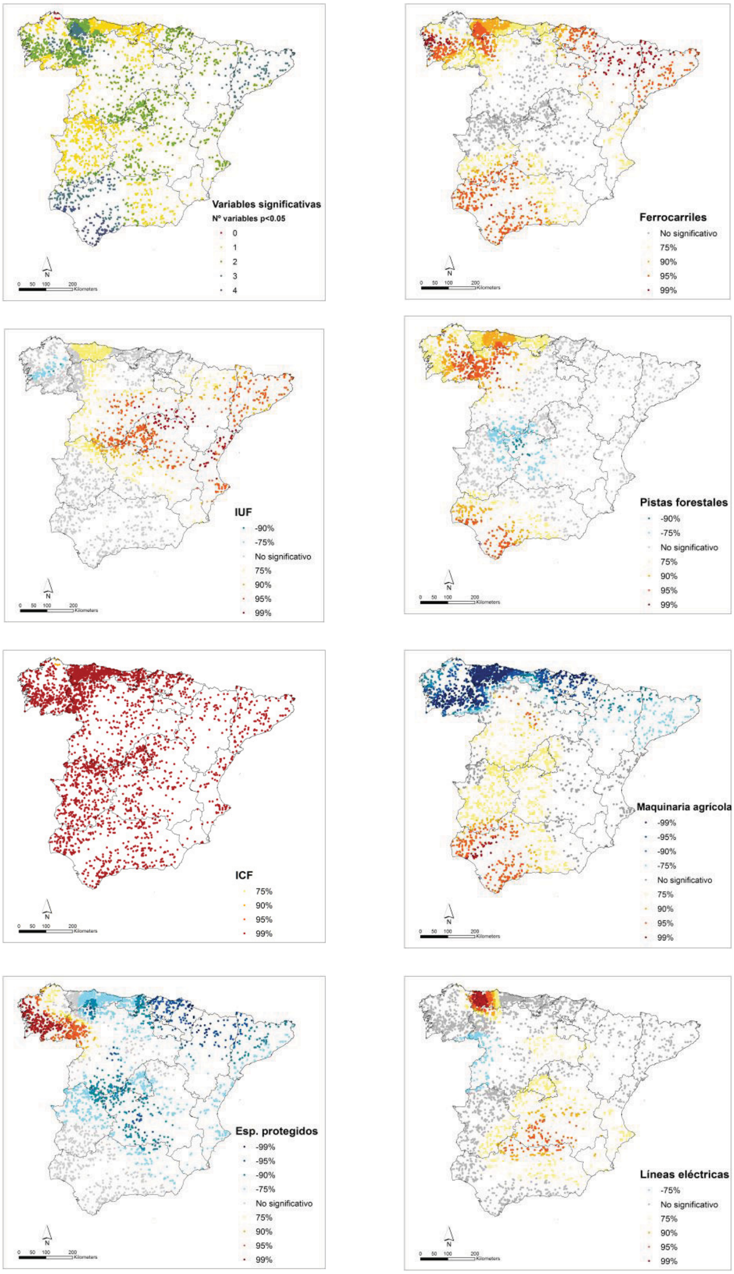

Figura 4. Umbrales de significación de las variables explicativas según la t de Student en el modelo GWLR.

Además de los umbrales de significación, en la figura 4 se presenta también la cartografía del número de variables significativas con p<0,05. Como se puede apreciar, siempre existe al menos una variable significativa en dicho umbral, siendo lo más habitual encontrar 2 o más variables.

Finalmente se presenta la cartografía de probabilidad de ocurrencia ligada a causalidad humana (figura 5). Atendiendo a dicha figura, los valores más elevados de probabilidad de ocurrencia se asocian a zonas de ICF, especialmente en el sector noroeste y en los bordes de las zonas montañosas, y a zonas de IUF, de gran importancia en la zona centro y el litoral mediterráneo. Estas dos variables, como ya se ha visto anteriormente, son las de mayor carga explicativa en el modelo atendiendo a valores de *t de Student*, siendo significativas a más del 95%, llegando en algunas zonas a más del 99%. La cartografía evidencia asimismo el carácter explicativo de algunas variables de implantación lineal como tendidos eléctricos, líneas de ferrocarril o pistas forestales.

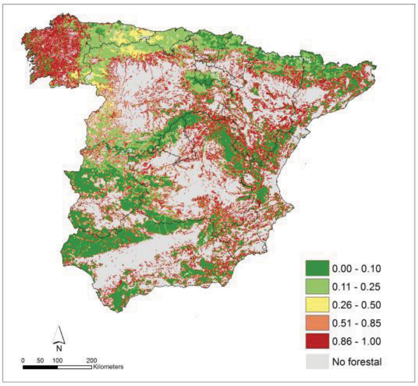

Figura 5. Probabilidad de ocurrencia de incendios forestales ligada a causalidad humana.

4 AJUSTE Y VALIDACIÓN DEL MODELO

A continuación se presentan los resultados obtenidos durante el proceso de validación. El R^2 local promedio obtenido de la muestra de calibración arroja un valor de 0,7, y un rango entre 0,19 y 0,85. Como se puede apreciar en la figura 6, los valores mínimos de R^2 se localizan en la Cornisa Cantábrica, principalmente en el Principado de Asturias. La presencia de valores tan bajos en esta zona se debe principalmente a que las variables ICF e IUF prácticamente no tienen representación espacial. Para tratar de corregir estos valores se han considerado diversas variables predictivas capaces de explicar la ocurrencia en esta área, concretamente se han ajustado varios modelos incluyendo las variables ganado no estabulado y la IPF. En el caso del ganado no estabulado, su contribución en los modelos ha resultado no significativa por lo que finalmente resultó descartada. En el caso de la IPF, pese a sí resultar significativa, su sentido explicativo según el valor de la *t de Student* era negativo, hecho que fue considerado incoherente y llevó a descartar también esta variable.

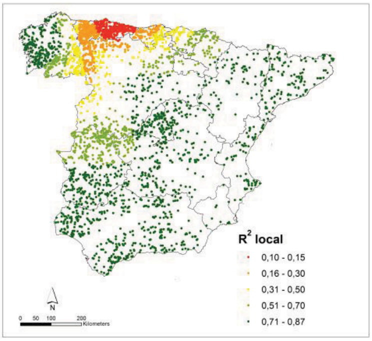

Figura 6. R^2 local.

En cuanto al porcentaje de acierto, en la tabla 1 se presenta su clasificación para los dos periodos de validación considerados. En el caso del periodo 1988-2007 el porcentaje de acierto global es de 87%, con un valor de *Kappa* de 0,73. A su vez, el acierto global obtenido utilizando la muestra 2008-2011 se sitúa en un 76%, con un valor de *Kappa* de 0,72. El menor porcentaje de acierto en la segunda muestra de validación se debe a que la predicción del modelo subestima la ocurrencia real del periodo, debido posiblemente a que el menor periodo de toma de datos distorsiona la clasificación de la densidad de ocurrencia como alta o baja al existir un número menor de registros.

1988-2007	**% Predicho**		
% Observado	Alta	Baja	% Marginal
Alta	31,4	11,5	42,9
Baja	1,5	55,5	57,1
% Marginal	33,0	67,0	100,0
2008-2011	**% Predicho**		
% Observado	Alta	Baja	% Marginal
Alta	27,7	22,7	50,4
Baja	1,4	48,2	49,6
% Marginal	29,2	70,8	100,0

Tabla 1. Clasificación del porcentaje de acierto. Arriba, periodo 1988-2007. Abajo, periodo 2008-2011.

5 COMPARACIÓN CON OTROS ESTUDIOS

En esta sección se presenta la comparación de los resultados obtenidos en el presente trabajo con los estudios realizados por Martínez *et al*. (2004) y Chuvieco *et al*. (2010).

En Martínez *et al*. (2004) se lleva a cabo la modelización de la probabilidad de ocurrencia de incendio por causa humana en todo el territorio español (excepto la Comunidad Foral de Navarra) a escala municipal utilizando técnicas de regresión logística binaria en el periodo 1988-2000. Las variables explicativas obtenidas como significativas en este trabajo son: densidad de maquinaria agrícola, densidad de parcelas agrícolas, densidad de entidades singulares de población, densidad de ganado en régimen extensivo y tasa de paro. El porcentaje global de acierto en la clasificación de la ocurrencia de incendio es de 85,9%.

En Chuvieco *et al*. (2010) se presenta un modelo de estimación del riesgo de incendio mediante la integración de distintas variables entre las que se encuentra la probabilidad de ocurrencia de incendio ligada a factores humanos en el periodo 1990-2004, utilizando técnicas de regresión logística. Dicha estimación se sirve, como unidad espacial de referencia, de una cuadrícula de 1x1 km^2. A diferencia de nuestro trabajo y del desarrollado por Martínez *et al.* (2004) el área de estudio se restringe a cuatro espacios considerados como representativos de la realidad de los incendios forestales en ambientes mediterráneos en España (Comunidad de Madrid, Comunidad Valenciana, provincia de Huelva y Aragón). Las variables socio-económicas obtenidas en las diferentes regiones de estudio consideradas así como el porcentaje de acierto en cada una de ellas son:

- Comunidad de Madrid: interfase urbano-forestal, espacios protegidos y tasa de paro. Porcentaje de acierto 70,6%.
- Comunidad Valenciana: tasa de variación de la población y potencial demográfico. Porcentaje de acierto 68,4 %.
- Provincia de Huelva: potencial demográfico, tasa de variación de la población agraria y buffer entorno a pistas forestales. Porcentaje de acierto 84,4 %.
- Aragón: interfase cultivo-forestal, cambio de uso del suelo, repoblaciones y buffer entorno a las líneas eléctricas. Porcentaje de acierto 86,8 %.

La metodología empleada en Chuvieco *et al*. (2010) es similar a la utilizada en este trabajo, exceptuando el uso de técnicas globales de regresión. En consecuencia, los resultados obtenidos son también similares en lo que refiere a las variables explicativas obtenidas en ambos modelos (IUF, ICF, espacios protegidos, líneas eléctricas y pistas forestales), si bien el porcentaje de acierto obtenido en este trabajo es superior, debido fundamentalmente a la utilización de GWLR. Por otra parte, a pesar de que Martínez *et al.* (2004) operan con una escala municipal, existen también ciertas semejanzas entre los resultados de estos autores y los nuestros, como es el caso de la presencia de variables de naturaleza estadística como la densidad de maquinaria agrícola. No obstante, aunque los porcentajes de acierto en la clasificación de la ocurrencia obtenidos en Martínez *et al.* (2004) y en este trabajo son prácticamente equivalentes, consideramos que nuestro resultado puede considerarse una mejora comparativa, en tanto en cuanto provee una mejor representación espacial de la probabilidad de ocurrencia.

6 CONCLUSIONES Y TRABAJO FUTURO

La utilización de técnicas GWR aplicadas a modelos LR ha permitido corroborar la elevada variación espacial existente en los factores explicativos asociados a la causalidad humana en incendios forestales. Asimismo, la validación de los resultados permite confirmar que tanto el método utilizado como los productos obtenidos son suficientemente consistentes, si bien el modelo todavía es mejorable en algunos aspectos ya que en algunas zonas –Asturias especialmente– se producen ciertos desajustes, debiéndose introducir aún alguna variable independiente que explique en mejor modo la ocurrencia, especialmente en relación con los incendios de pasto-matorral de febrero-marzo.

Como trabajo futuro se prevé la exploración tanto de nuevas variables predictivas como de nuevos métodos de espacialización de las mismas (distancia hasta la interfase, cartografía de densidad…). Se desarrollarán además nuevos modelos temporalmente dinámicos a escala estacional, con el propósito de averiguar si existen diferencias significativas en los factores explicativos ligados a la ocurrencia en diferentes periodos del año, o incluso de mayor detalle.

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APPENDIX E. PROPUESTA METODOLÓGICA PARA LA MODELIZACIÓN DE LA RESILIENCIA DE LA VEGETACIÓN AFECTADA POR INCENDIOS FORESTALES EN ESPAÑA

This appendix introduces the first steps of the quantitative assessment of the ecological vulnerability of plant communities affected by fire.

Propuesta metodológica para la modelización de la resiliencia de la vegetación afectada por incendios forestales en España

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RESUMEN

El presente trabajo tiene como objetivo modelar mediante técnicas SIG la resiliencia de las comunidades vegetales frente a los efectos del fuego. Para ello se ha diseñado una metodología, basada en álgebra de mapas, que permite el cálculo del tiempo aproximado necesario para que la vegetación recupere un estado similar a las condiciones previas al impacto de un incendio. El método propuesto considera, por un lado, la vegetación presente en el territorio, caracterizada en términos de estructura (arbolado, matorral o pasto) y estrategia reproductiva (rebrotadoras o germinadoras); por otro, se consideran dos de los principales factores que condicionan el tiempo de recuperación: la disponibilidad hídrica y la pérdida de suelo. Asimismo, se ha tenido en cuenta la influencia en la disponibilidad hídrica y en la pérdida de suelo de posibles cambios a medio plazo en los regímenes de precipitación, a través de tendencias estacionales observadas y modelizadas espacialmente durante el periodo 1946-2005. La metodología se ha aplicado a la España continental, dentro del contexto del proyecto FIREGLOBE. Los resultados sugieren un tiempo de regeneración que oscila entre dos años en comunidades de pastizal, hasta alrededor de 100 años en comunidades de arbolado de baja germinación. Existen además contrastes significativos en la distribución geográfica del tiempo de regeneración, principalmente entre las regiones biogeográficas Eurosiberiana y Mediterránea.

PALABRAS CLAVE

Resiliencia, incendios forestales, comunidades vegetales, modelado SIG, tendencias.

ABSTRACT

This study aimed to estimate the resilience of plant communities after experiencing the effects of fire. For this we designed a methodology, based on map algebra and a Geographical Information System, which allowed the calculation of the approximate time required to restore vegetation to similar to pre-fire conditions, from the point of view of plant characteristics: plant height and canopy cover. To this end, the proposed methodology considered, on one hand, the vegetation present in the territory, characterized in terms of structure (tree, shrubland or grassland) and reproductive strategy (resprouter or seeder); and on the other hand, two of the main factors that determine resilience time: water availability and soil loss – also considering the influence on both of observed rainfall trends during the last 50 years. The methodology was applied to the continental Spain within the framework of the FIREGLOBE project. The results suggest an indicative resilience time from two to around 100 years in grassland communities and tree communities with low germination, respectively. There were significant contrasts in the geographical distribution of the vegetation regeneration time, mainly between Euro-Siberian and Mediterranean bio-geographical regions.

KEY WORDS

Resilience, wildfires, plant communities, GIS modeling, trends.

1 INTRODUCCIÓN

La Europa mediterránea es uno de los territorios más afectados por incendios forestales de acuerdo a las estadísticas publicadas por la Comisión Europea (EC, 2010). En España, la superficie total quemada ha disminuido durante los últimos 25 años, mientras que el número de incendios ha aumentado (San-Miguel *et al*., 2012). Además, resulta previsible que se sucedan, cada vez con mayor frecuencia, años con temporadas de incendio dramáticas, similares a las que varios países como Portugal, Grecia o Australia han sufrido en la última década, como consecuencia de olas de calor extremas debidas, entre otros motivos, a cambios en los patrones climáticos. Por lo tanto, es necesario tanto mejorar los sistemas de prevención de incendios, como fomentar la evaluación de los posibles daños potenciales en los ecosistemas naturales, promoviendo así la conservación de los servicios de valor económico, ambiental, cultural y estético que éstos proporcionan a la sociedad (Costanza *et al*., 1997). En este sentido la evaluación de la vulnerabilidad ecológica supone un interesante apoyo a los servicios de extinción y prevención, siendo especialmente relevante cuando la falta de información espacializada sobre vulnerabilidad supone un obstáculo en la identificación de áreas prioritarias para la implantación de medidas de protección y restauración (Hannah *et al*., 2002; Brooks *et al*., 2006).

La estimación de la resiliencia de la vegetación frente a incendios forestales está justificada en tanto en cuanto el fuego es uno de los principales agentes transformadores en una amplia variedad de ecosistemas (FAO, 2007). Esto es particularmente cierto en el caso de los ecosistemas mediterráneos, donde el fuego es la principal perturbación de carácter natural, desempeñando además un papel decisivo en la dinámica y estructura de comunidades tanto vegetales como animales (di Castri y Mooney 1973; Naveh 1975; Trabaud y Lepart 1980; Gill *et al*., 1981). La comprensión de la relación entre paisaje y fuego se encuentra, entre otros factores, en la estimación de la resiliencia post-fuego de los ecosistemas (Arianoutsou *et al*., 2011).

Este trabajo se centra en la evaluación de la resiliencia de las comunidades vegetales tras el fuego, definida como una medida de la velocidad a la que la vegetación vuelve al equilibrio después de un incendio forestal (de Lange *et al*., 2010). En este sentido, la vegetación, pese a ser el elemento más afectado por la incidencia de incendios (calcinación, defoliación…), es el factor, dentro de los de carácter estructural, con mayor influencia sobre las características de los procesos de reconstrucción del medio ambiente. Esta influencia se manifiesta en dos aspectos: en primer lugar, la vegetación desempeña un papel muy importante en la determinación de la cantidad de biomasa que se regenera después del fuego, aunque, obviamente, en el proceso de regeneración post-fuego intervienen otros factores ambientales, ya sea individualmente o en combinación; en segundo lugar, las comunidades existentes determinan las características del punto de partida en el proceso de reconstrucción tras el incendio.

Para evaluar la resiliencia de la vegetación a escala regional se ha diseñado una metodología basada en álgebra de mapas y un Sistema de Información Geográfica (SIG) que permite la estimación del tiempo aproximado necesario para retornar a condiciones similares a las anteriores al impacto del fuego. No obstante, la respuesta de la vegetación al fuego es un proceso complejo y difícil de generalizar, ya que implica la consideración de un elevado número de variables de naturaleza diversa, como la composición florística, la intensidad de las precipitaciones, las características del suelo, la severidad del fuego o las condiciones climáticas post-incendio.

Nuestra metodología permite estimar el tiempo de recuperación de la vegetación a través de la integración de algunos de los principales factores o procesos que influyen en el desarrollo de la vegetación después del fuego como la estructura de la vegetación, la estrategia reproductiva, la disponibilidad hídrica y la pérdida de suelo. Los dos primeros refieren a características intrínsecas de la vegetación, que definen su capacidad de crecimiento (Alloza, 2006; de la Riva *et al*., 2008) y cuya valoración se basa en la dicotomía entre especies rebrotadoras y germinadoras (Pausas *et al*., 2008). Los dos últimos son parámetros que dependen de las características y la evolución temporal de los factores ambientales, que influyen en la regeneración vegetal mediante la modificación de la cantidad de agua o nutrientes disponibles, o alterando la composición química del suelo (Shakesby y Doerr 2006). Asimismo, se ha tenido en cuenta la influencia en la disponibilidad hídrica y en la pérdida de suelo de posibles cambios a medio plazo en los regímenes de precipitación, a través de tendencias estacionales observadas y modelizadas espacialmente durante el periodo 1946-2005 por de Luis *et al*. (2010). El método propuesto tiene como objetivo ser una herramienta útil para estimar la resiliencia de la vegetación después del fuego a escala regional, basado en la interacción de un número reducido de variables. Este método se centra en la obtención de un resultado cuantitativo, en un escenario de máxima severidad de incendios. No obstante, en ningún momento se pretende ofrecer valores de tiempo categóricos, sino proporcionar un resultado indicativo más preciso que el análisis cualitativo. Esta metodología ya ha sido implementada con éxito como parte de la evaluación del riesgo de incendio llevado a cabo por el equipo del proyecto FIREGLOBE (Chuvieco *et al*., 2011) durante la temporada de incendios en el verano de 2011.

2 METODOLOGÍA

La metodología para estimar la capacidad de recuperación de la vegetación post-incendio (RT, *Resilience Time*) se basa en el cálculo del tiempo de regeneración de las comunidades vegetales, es decir, el tiempo aproximado necesario para llegar a condiciones que pudieran garantizar el desarrollo de la vegetación hasta recuperar condiciones similares a las existentes previamente al impacto del fuego. Esta metodología se basa en la asignación de un tiempo de recuperación inicial (RTOC, *Resilience Time in Optimum Conditions*) en función de las características de la vegetación en términos de estructura y estrategia reproductiva, considerando que existen unas condiciones óptimas para el desarrollo de las comunidades vegetales. A continuación, se calcula el aumento del tiempo de regeneración introduciendo la influencia de los factores limitantes (VGC, *Vegetation Growth Constraints*): disponibilidad de agua y pérdida de suelo. Los VGC se modifican a su vez considerando el efecto de las tendencias observadas en la precipitación durante los últimos 50 años. La figura 1 muestra un diagrama de flujo del proceso seguido para el cálculo del tiempo de recuperación.

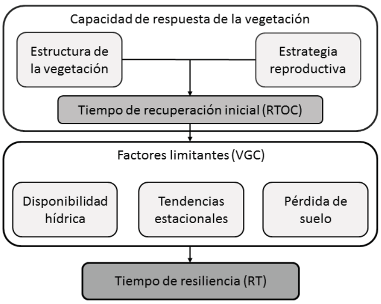

Figura 1. Flujo de trabajo para el cálculo del tiempo de recuperación.

La metodología ha sido implementada en un entorno SIG para calcular la resiliencia mediante álgebra de mapas y herramientas de análisis espacial. La resolución espacial tanto de los datos de entrada como del producto final es de 1x1 km, excepto en el caso de las tendencias en la precipitación que han sido generadas a una resolución de 15x15 km.

En las siguientes secciones se describe detalladamente el proceso seguido y las fuentes de datos utilizadas para el desarrollo del método propuesto, empezando por la asignación del RTOC, seguido de la descripción de los VGC y, finalmente, el cálculo de RT.

2.1 RTOC

Inicialmente, la evaluación de RT se realiza a partir de la lista de especies vegetales del *Mapa Forestal de España* (MARM, 1997). Esto ha requerido la caracterización, en términos de su estructura y estrategia reproductiva, de más de 500 especies. Esta caracterización se basa en estudios previos sobre regeneración y respuesta de la vegetación post-incendio, como Tárrega y Luis-Calabuig (1989), Trabaud (1990, 1998, 2002), Vera de la Fuente (1994), Barbéro *et al.* (1998), Pausas *et al.* (2004), Buhk *et al.* (2007) y Baeza y Roy (2008). Una vez realizada la clasificación se asigna un tiempo inicial de regeneración, considerando que la recuperación de la vegetación se produce en ausencia de factores limitantes para su desarrollo. Cabe señalar que el tiempo inicial asignado no pretende ser un valor categórico ya que dicho tiempo puede variar significativamente dependiendo de las características locales y del papel jugado por factores circunstanciales. La tabla 1 muestra las combinaciones de estructura y estrategia reproductiva resultantes, así como el RTOC asignado a cada una de ellas. En la figura 2 se presenta su cartografía.

Estructura/estrategia reproductiva	**RTOC (años)**
Pasto	2
Matorral rebrotador	6
Matorral germinador	10
Arbolado de alta germinación	25
Arbolado rebrotador	30
Arbolado de baja germinación	45

Tabla 1. RTOC en función de la estructura de la vegetación y su estrategia reproductiva.

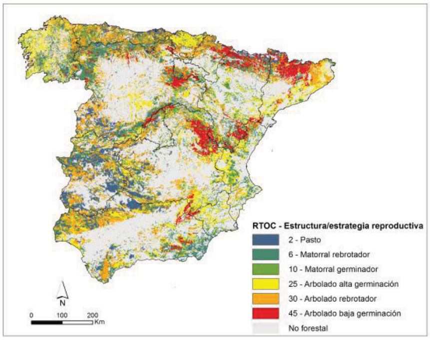

Figura 2. RTOC en función de la estructura de la vegetación y su estrategia reproductiva.

En términos generales se ha considerado que las especies germinadoras tienen menor capacidad de recuperación que las rebrotadoras, debido principalmente a la potencial destrucción del banco de semillas como consecuencia del incendio. Asimismo, en el caso del arbolado se ha hecho distinción entre alta o baja capacidad de germinación en función de la tasa de generación de semillas. La vegetación que utiliza ambos mecanismos de reproducción (rebrotadoras facultativas según Naveh, 1975 y Buhk *et al.*, 2007) se ha clasificado como rebrotadora al considerar que es el mecanismo más ventajoso.

2.2 VGC

En esta sección se describe el proceso seguido para obtener los VGC.

2.2.1 Disponibilidad hídrica

El incremento en el RTOC, dependiendo de la disponibilidad de agua (F_w), ha sido calculado a partir del mapa de series de vegetación (Rivas y Gandullo, 1987). El concepto de serie de vegetación hace referencia al conjunto ordenado de las comunidades vegetales que pueden ser remplazadas en el tiempo en un lugar específico (Bolós, 1962). El mapa de series de vegetación delimita las unidades de vegetación reconocidas, con el fin de determinar la diversidad de ecosistemas forestales en España. Cada una de las diferentes series presenta una categoría típica de lluvias u ombroclima (árido, semiárido, seco, sub-húmedo, húmedo e hiper-húmedo), basada en la precipitación anual. La disponibilidad de agua se ha evaluado mediante la agrupación de estos ombroclimas, recodificados más tarde a un valor numérico representativo del factor de incremento (*Fw*) en el proceso de regeneración. El uso de este mapa es particularmente adecuado para la consecución de los objetivos de este trabajo, ya que en la delimitación de las series de vegetación potencial se consideraron parámetros tanto de carácter orográfico como bioclimático. La tabla 2 y la figura 3 muestran la correspondencia entre los intervalos de precipitación y la proporción de aumento del RTOC (asignado siguiendo el criterio de los autores del presente trabajo).

Ombroclima	Precipitación (mm)	F_w
Hiper-húmedo	>1600	0.000
Húmedo	1000-1600	0.075
Sub-húmedo	600-1000	0.150
Seco	350-600	0.600
Árido-semiárido	<350	1.200

Tabla 2. Ombroclimas, precipitación anual y F_w.

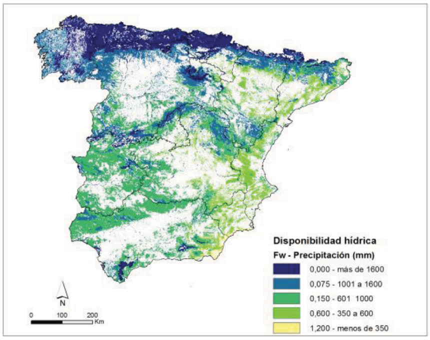

Figura 3. F_w en función de la precipitación anual.

2.2.2 Pérdida de suelo

La evaluación del incremento RT como función de la pérdida de suelo (F_e) se ha llevado a cabo mediante el análisis de la distribución espacial de la erosión del suelo en condiciones post-incendio. Para este fin se ha utilizado el *Pan European Soil Erosion Risk Assessment model* (PESERA), un modelo espacialmente distribuido para cuantificar la erosión hídrica del suelo; desarrollado para proporcionar información acerca del riesgo de erosión a nivel europeo, es un modelo conservador, que considera distintos componentes determinantes de la erosión, como los factores climáticos, la vegetación o la topografía (Kirkby *et al.*, 2004). Este modelo puede ser utilizado como una herramienta a nivel regional, comparable a otras como la USLE (Wischmeier y Smith, 1960), pero con una mejor adaptación a la realidad del medio ambiente en Europa. Los resultados del modelo están validados a escala de cuenca y han sido comparados con datos obtenidos mediante diferentes métodos de medición de la erosión. En el contexto de este trabajo, los indicadores de erosión del suelo no sólo proporcionan información acerca de este proceso, sino que permiten relacionar los distintos factores que causan la erosión mediante la simulación de diferentes escenarios climáticos y/o de uso del suelo.

En este trabajo se ha utilizado el subconjunto español de la cartografía de PESERA, si bien se han realizado modificaciones en relación con los procesos de erosión que siguen los incendios forestales. Una extensa revisión bibliográfica revela una gran incertidumbre sobre el efecto en la erosión de la pérdida de cubierta vegetal como resultado de fuego. Los incrementos de tasa de erosión van desde un aumento de 18,6 (Soto *et al.*, 1994; Soto y Díaz-Fierros, 1998) a 5200 (Shakesby *et al.*, 1994, 2002; Shakesby, 2011) veces la tasa de erosión inicial. Teniendo en cuenta la gran heterogeneidad de estos valores (posiblemente debido a diferencias tanto en las condiciones locales donde se llevaron a cabo los experimentos como a su diseño o a las técnicas de medición empleadas), se ha usado el modelo ERMiT (Robichaud *et al.*, 2006) para modificar las tasas de erosión pre-incendio reportadas en PESERA. El modelo ERMiT integra información sobre indicadores de clima, suelo (textura), topografía (pendiente y longitud de la pendiente), además del tipo de vegetación afectada y el nivel de severidad del incendio, lo que permite realizar simulaciones para evaluar la variación en las tasas de erosión. El modelo utiliza un método probabilístico que incorpora la variabilidad temporal y espacial en el clima, las propiedades del suelo y la severidad de la quema según distintos tipos estructurales (bosque, pasto y matorral de montaña). Las simulaciones con el modelo ERMiT se llevaron a cabo en varios lugares considerados representativos de cada región bioclimática en España, desarrollando además escenarios con diferentes combinaciones de estructura de la vegetación y pendiente. En la tabla 3 se presentan los factores de incremento promedio sobre la tasa de erosión pre-fuego. Analizando en detalle los factores de incremento reportados en dicha tabla, resulta llamativo que en comunidades de arbolado los factores de incremento más elevados se han obtenido en zonas de baja pendiente, cuando lo esperable sería quizás lo contrario. No obstante, hay que tener en cuenta que este factor de incremento es un valor relativo siendo el valor de incremento bruto (tasa de erosión) es en todos los casos mayor cuanto más acusada es la pendiente.

		Región mediterránea	
Estructura	**Pendiente** (%)	**Año 1**	**Año 2**
Arbolado	< 15	1,60	1,20
	15-45	1,55	1,15
	>45	1,55	1,15
Matorral	< 15	1,60	1,20
	15-45	1,60	1,20
	>45	1,60	1,20
Pasto	< 15	1,60	1,15
	15-45	1,55	1,20
	>45	1,55	1,15
		Región eurosiberiana	
Estructura	**Pendiente** (%)	**Año 1**	**Año 2**
Arbolado	< 15	1,80	1,15
	15-45	1,60	1,15
	>45	1,60	1,15
Matorral	< 15	1,55	1,20
	15-45	1,55	1,20
	>45	1,60	1,20
Pasto	< 15	1,50	1,20
	15-45	1,50	1,15
	>45	1,50	1,15

Tabla 3. Factor de incremento de las tasas de erosión pre-incendio, calculado por región bioclimática, estructura de la vegetación y pendiente del terreno.

De acuerdo con esto, las tasas de erosión de PESERA se modifican a través del factor de incremento obtenido de las simulaciones mediante ERMiT siguiendo la ecuación:

$$E_f = \Sigma_y \Sigma_s E_{\mathrm{Pre}} F_{re} \qquad (1)$$

Donde E_f es la tasa de erosión corregida, E_P es la tasa de erosión pre-fuego, *F* es el factor de incremento post-fuego, *r* es la región bioclimática, *e* es la estructura de la vegetación, *s* es el intervalo de pendiente.

Una vez corregidas las tasas de erosión, los valores obtenidos se agrupan en cinco intervalos que serán posteriormente reclasificados en factores de incremento de RTOC (siguiendo el criterio de los autores del presente trabajo). En la tabla 4 y la figura 4 se presenta los intervalos de erosión, su F_e asociado y su cartografía.

Tasa de erosión post-fuego (ton ha^{-1} año^{-1})	F_e
<0,04	0.000
0,05 – 0,13	0.075
0,14 – 0,36	0.150
0,37 – 0,86	0.225
>0,86	0.325

Tabla 4. Tasa de erosión post-fuego y F_e asociado.

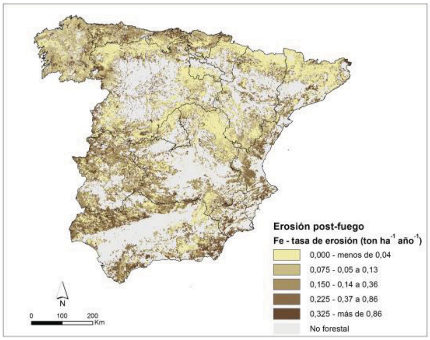

Figura 4. Tasa de erosión post-fuego y F_e asociado.

2.2.3 Tendencias en la precipitación

Las tendencias climáticas son un factor clave en la evaluación de la vulnerabilidad (González *et al.*, 2010; Ruiz *et al.*, 2011). Las tendencias detectadas en la precipitación se incluyen en el cálculo de RT como un factor de ponderación de los dos anteriores VGC. En este sentido, se considera que una disminución en la precipitación (tendencia negativa) debería implicar una disminución en la disponibilidad de agua y, por lo tanto, la influencia de la falta de agua aumenta. Un comportamiento similar se espera en el caso de la erosión del suelo, pero en sentido contrario. Un aumento en la precipitación (tendencia positiva) debería aumentar su influencia en RT, al aumentar la eficiencia de la erosión hídrica y por tanto la pérdida de suelo. Para incluir esto en el modelo de cálculo de RT se utilizan las tendencias observadas en la precipitación en el trabajo de Luis *et al.* (2010), donde se analiza la variabilidad espacial de los regímenes estacionales de precipitación en la Península Ibérica para un período temporal de observaciones de 50 años, desde 1946 hasta 2005, utilizando el *test de Mann-Kendall*. La variabilidad espacial de las tendencias se ha caracterizado de acuerdo al signo y el nivel de significación de las tendencias observadas. Debido a que las tendencias de precipitación se calcularon sólo a nivel estacional, hemos utilizado las tendencias de invierno para la ponderación de la disponibilidad hídrica, teniendo en cuenta que es la estación más eficaz para la captación de agua por parte de la vegetación debido a la baja evapotranspiración potencial; y las tendencias de otoño para la ponderación de la erosión del suelo ya que ésta es la estación más crítica debido a la sequedad del suelo después del verano y la reducción de la cubierta vegetal consecuencia de la pérdida de hojas en las comunidades de hoja caduca. El valor de ponderación varía entre 1, cuando no se observa una tendencia significativa ($p>0,30$), y 2, cuando ésta lo es al 1% ($p<0.01$). Las figuras 5 y 6 muestran la distribución espacial de las tendencias en invierno y otoño, los niveles de significación y los factores de ponderación (T_w invierno y T_a otoño) aplicados a los VGC correspondientes.

2.3 RT

El RT se calcula como la suma de RTOC y los incrementos en el tiempo de recuperación debido a disponibilidad hídrica y pérdida de suelo, ponderados en función de las tendencias observadas en la precipitación.

$$RT = RTOC + T_{Fw} T_w + T_{Fe} T_a \qquad (2)$$

Donde *RT* es el tiempo de recuperación, *RTOC* es el tiempo de recuperación en condiciones óptimas, T_{Fw} es el incremento de tiempo asociado a la disponibilidad hídrica, T_w es el factor de ponderación en función de las tendencias en la precipitación de invierno, T_{Fe} es el incremento de tiempo asociado a la pérdida de suelo y T_a es el factor de ponderación en función de las tendencias en la precipitación de otoño.

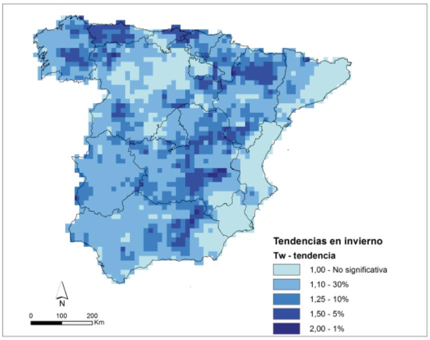

Figura 5. Tendencias observadas en la precipitación de invierno durante el periodo 1946-2005 y T_w. Fuente: de Luis et al. (2010).

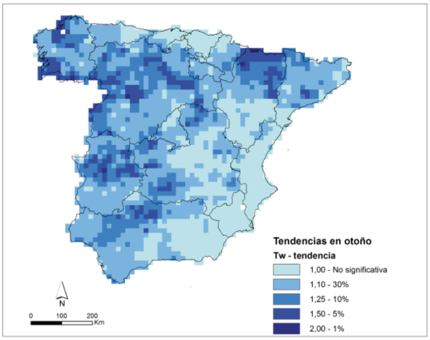

Figura 6. Tendencias observadas en la precipitación de otoño durante el periodo 1946-2005 y T_a. Fuente: de Luis et al. (2010).

3 RESULTADOS

A continuación se presentan los resultados obtenidos de la aplicación de la metodología propuesta a la España peninsular. En las figuras. 7 y 8 se presentan por una parte el RT obtenido y el porcentaje de contribución de los VGC. En la tabla 4 se presenta un resumen estadístico de los resultados en función de las categorías establecidas para la asignación del RTOC.

Los resultados sugieren un RT que oscila entre los dos años en las comunidades de pastizal y alrededor de 100 años en las comunidades de arbolado de baja germinación. Sin embargo, existen contrastes significativos en la distribución geográfica de la resiliencia, principalmente entre las regiones bio-geográficas eurosiberiana y mediterránea.

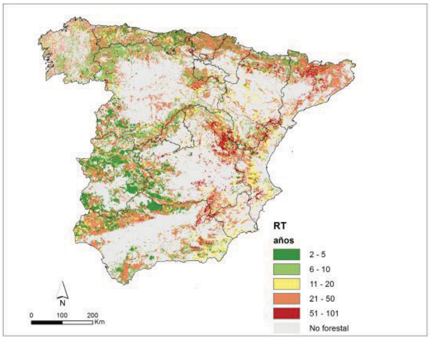

Figura 7. Cartografía de la resiliencia (RT).

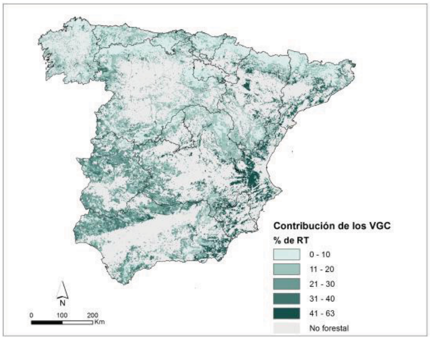

Figura 8. Contribución de los VGC en el RT.

La región eurosiberiana presenta valores más bajos de RT debido a la mayor disponibilidad hídrica como resultado del clima Atlántico presente en esta región de España. Por otra parte, en la región mediterránea, sobre todo en la costa mediterránea, es donde se localizan los períodos más largos de recuperación. Esto se produce como consecuencia de la baja disponibilidad de agua debido a la escasa precipitación y también a la agresividad climática, que produce eventos torrenciales relativamente frecuentes, aumentando así la pérdida de suelo. Sin embargo, aunque los VGC tienen un peso importante en el tiempo de reconstrucción, su participación en el RT es de aproximadamente un 22% del RT, si bien en zonas donde las tendencias en la precipitación son significativas con p<0,01 su contribución supera el 60% del RT. Así pues, el tipo y características de la vegetación parecen ser el parámetro más importante en el proceso de recuperación post-incendio.

Comunidad vegetal	Min	Max	Avg	Std
Pasto	2	5,4	2,6	0,42
Matorral rebrotador	6	16,2	8,2	2,00
Matorral germinador	10	26,9	13,6	2,88
Arbolado alta germ	30	78,4	38,5	6,84
Arbolado rebrotador	25	67,4	35,9	7,87
Arbolado baja germ.	45	100,7	52,9	7,85

Tabla 4. Resumen estadístico de los resultados.

4 CONCLUSIONES

Nuestros resultados indican que existe una elevada heterogeneidad en los valores de RT, tanto entre las comunidades vegetales consideradas como entre las diferentes regiones de la España peninsular. Esto no es sorprendente, ya que este territorio presenta importantes contrastes desde un punto de vista físico o ambiental. Si bien las principales diferencias se encuentran entre las dos regiones biogeográficas (eurosiberiana y la mediterránea), también encontramos contrastes relevantes dentro de cada una de ellas, directamente vinculados a la variabilidad espacial en las características del terreno y las condiciones climáticas. Este hecho aumenta la complejidad de los análisis de parámetros ambientales o procesos, especialmente a escala regional.

Sin embargo, consideramos que los valores obtenidos de RT se ajustan adecuadamente a la evolución esperada de las comunidades vegetales tras un incendio de alta severidad. En cualquier caso, el método propuesto es lo suficientemente robusto para ser de utilidad en varios campos de estudio, tales como la ordenación territorial, los incendios forestales o la evaluación de la vulnerabilidad socioeconómica o de servicios ambientales. Esto se debe principalmente a la simplicidad del método propuesto, que requiere pocas variables, pero representativas del fenómeno analizado. Además, el estar integrado dentro de un SIG permite no sólo la cartografía de los resultados, sino también el desempeño de diferentes tipos de análisis espacial y cartográfico.

La metodología ya ha sido implementada con éxito como parte de la evaluación del riesgo de incendio llevado a cabo por el equipo del proyecto FIREGLOBE durante la temporada de incendios en el verano de 2011.

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