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Adrián Jiménez Ruano

Characterizing pyroregions in mainland Spain from spatial-temporal patterns of fire regime and their underlying drivers

Departamento
Geografía y Ordenación del Territorio

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El autor de esta tesis doctoral disfrutó para su desarrollo, así como para la estancia en un centro de investigación extranjero, de la financiación del *Programa de ayudas FPU del Ministerio de Educación, Cultura y Deporte*. Referencia de la ayuda FPU 13/06618. Desea hacer constar, por tanto, su agradecimiento.

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Deseo expresar mi más sincero agradecimiento al Dr. Juan de la Riva por contar conmigo desde el principio y brindarme la oportunidad de trabajar juntos, gracias por esas charlas conceptuales y de perspectiva generales tan necesarias, y por haber velado siempre por el correcto desarrollo de la investigación y el manteamiento del hilo conductor.

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A Matt Jolly por su cálida y memorable acogida durante mi estancia en Estados Unidos, muchas gracias por tratarme como parte de tu pequeña gran familia. Quiero agradecer profundamente la energía, serenidad y motivación que me has trasmitido, no solo en lo profesional, sino también en lo personal.

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A mi familia y amigos de siempre por estar ahí a pesar de la insalvable distancia. Gracias por escucharme y darme aliento cuando sentía que me fallaban las fuerzas. En especial a Francisco Javier Rubio, por sus charlas motivadoras en los indecisos y duros comienzos de la investigación.

Asimismo, agradezco a los revisores anónimos de mis artículos por sus valiosos comentarios que han mejorado notablemente la calidad de mis manuscritos.

This thesis has been elaborated in the fashion of compendium of publications. The PhD candidate, Adrián Jiménez Ruano, is listed as first author and responsible of almost all the articles. The works that constitute the body of the thesis, its impact factor and detail of the tasks carried out by each of the co-authors in each one are as follows:

Jiménez-Ruano A, Rodrigues M, de la Riva J (2017) Understanding wildfires in mainland Spain. A comprehensive analysis of fire regime features in a climate-human context. ***Applied Geography*** 89:100-111. https://doi.org/10.1016/j.apgeog.2017.10.007

JCR Impact factor: 3.117 (Q1, "Geography")

In this work, the PhD student, Adrián Jiménez Ruano, is responsible for most of the work, having carried out the statistical and spatial analysis, and being the main responsible for writing all contents. Dr. Marcos Rodrigues Mimbrero collaborated with the development of some tasks and also helped in the writing process. Both Dr. Juan de la Riva and Marcos Rodrigues Mimbrero are responsible of the general research topic and have collaborated in reviewing the results.

Jiménez-Ruano A, Rodrigues M, de la Riva J (2017) Exploring spatial–temporal dynamics of fire regime features in mainland Spain. ***Natural Hazards and Earth System Sciences*** 17:1697-1711. https://doi.org/10.5194/nhess-17-1697-2017

JCR Impact factor: 2.281 (Q2, "Geosciences, Multidisciplinary")

In this work, the PhD student, Adrián Jiménez Ruano, is responsible for most of the work, having carried out the statistical and spatial analysis, and being the main responsible for writing all contents. Dr. Marcos Rodrigues Mimbrero and Dr. Juan de la Riva also collaborated closely in reviewing the methodology and results.

Jiménez-Ruano A, Rodrigues M, Jolly W.M, de la Riva J (2019) The role of short-term weather conditions in temporal dynamics of fire regime features in mainland Spain. ***Journal of Environmental Management*** 241:575-586 https://doi.org/10.1016/j.jenvman.2018.09.107

JCR Impact factor: 4.865 (Q1, "Environmental Sciences")

In this work, the PhD student, Adrián Jiménez Ruano, is responsible for most of the work, having carried out the statistical and spatial analysis, and being the main responsible for writing all contents. Dr. Matt Jolly appears as co-author for his collaboration in the construction of part of the methodology and review of the preliminary results and is also responsible for the research stay in which the research was carried out. Dr. Marcos Rodrigues Mimbrero and Dr. Juan de la Riva also collaborated closely on reviewing of results.

Rodrigues M, **Jiménez-Ruano A**, de la Riva J. (2016) Analysis of recent spatial–temporal evolution of human driving factors of wildfires in Spain. ***Natural Hazards*** 84(3):2049-2070. https://doi.org/10.1007/s11069-016-2533-4

JCR Impact factor: 1.833 (Q2, "Geosciences, Multidisciplinary")

In this work, the Dr., Marcos Rodrigues, is responsible for most of the work, having carried out the statistical and spatial analysis, and being the main responsible for writing all contents. The PhD student, Adrián Jiménez Ruano has collaborated in executing part of the methodology. Dr. Juan de la Riva is responsible of the general research topic and have collaborated in reviewing the results.

Rodrigues M, **Jiménez-Ruano A**, Peña-Angulo D, de la Riva J. (2018) A comprehensive spatial-temporal analysis of driving factors of human-caused wildfires in Spain using Geographically Weighted Logistic Regression. ***Journal of Environmental Management*** 225: 177-192. https://doi.org/10.1016/J.JENVMAN.2018.07.098

JCR Impact factor: 4.865 (Q1, "Environmental Sciences")

In this work, the Dr., Marcos Rodrigues, is responsible for most of the work, having carried out the statistical and spatial analysis, and being the main responsible for writing all contents. The PhD student, Adrián Jiménez Ruano has collaborated in executing part of the methodology and some cartography for the final paper. Dr. Peña-Angulo has provided the climate data employed in the research. Dr. Juan de la Riva is responsible of the general research topic and have collaborated in reviewing the results.

In addition, other works have been included as the body of the research, but they have not yet been published:

Rodrigues M, **Jiménez-Ruano A**, de la Riva J (Under review). Fire regime dynamics in mainland Spain. Part 1: drivers of change. ***Science of the Total Environment.***

JCR Impact factor: 5.589 (Q1, "Environmental Sciences")

In this work, the Dr 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 all contents. The PhD student, Adrián Jiménez Ruano, has collaborated very closely in elaboration of the methodological process and in obtaining part of the results. Dr. Juan de la Riva has also actively participated in the review of the results.

Jiménez-Ruano A, de la Riva J, Rodrigues M (Under review). Fire regime dynamics in mainland Spain. Part 2: a near-future prospective of fire activity. ***Science of the Total Environment.***

JCR Impact factor: 5.589 (Q1, "Environmental Sciences")

In this work, the PhD student, Adrián Jiménez Ruano, is responsible for most of the work, having carried out the statistical and spatial analysis, and being the main responsible for writing all contents. Dr. Marcos Rodrigues has collaborated very closely in the preparation of the final methodological process and the review of the text, and Dr. Juan de la Riva has also participated closely on reviewing the results.

Finally, several conference contributions have been included in two specific appendices:

Appendix D

Jiménez-Ruano A, Rodrigues M, de la Riva Fernández J. 2018. Identifying pyroregions by means of Self Organizing Maps and hierarchical clustering algorithms in mainland Spain, in: Viegas, D.X. (Ed.), ***Advances in Forest Fire Research*** (VIII International Conference on Forest Fire Research). Imprensa da Universidade de Coimbra, Coimbra, pp. 495–505. https://doi.org/https://doi.org/10.14195/978-989-26-16-506_54

In this work, the PhD student, Adrián Jiménez Ruano, is responsible for most of the work, having carried out the statistical and spatial analysis, and being the main responsible for writing all contents. Dr. Marcos Rodrigues has collaborated very closely in the preparation of the methodological process and in the review of the writing. Dr. Juan de la Riva has also participated closely on reviewing the results.

Appendix E

Jiménez-Ruano A, Rodrigues M, de la Riva Fernández J. (2017). An analysis of wildfire frequency and burned area relationships with human pressure and climate gradients in the context of fire regime. ***Geophysical Research Abstracts*** (Poster contribution). Vol. 19 EGU2017-15084, Vienna, Austria.

In this work, the PdD student, Adrián Jiménez Ruano, is responsible for most of the work, having carried out the statistical and spatial analysis, and being the main responsible for elaborating the poster. Dr. Marcos Rodrigues has collaborated very closely in the conception of the methodology and in the review of the poster design. Dr. Juan de la Riva has also participated on reviewing the results.

Jiménez-Ruano A, Rodrigues M, de la Riva Fernández J. (2017). Assessing the influence of small fires on trends in fire regime features at mainland Spain. ***Geophysical Research Abstracts*** (Poster contribution). Vol. 19, EGU2017-15755, Vienna, Austria.

In this work, the PdD student, Adrián Jiménez Ruano, is responsible for most of the work, having carried out the statistical and spatial analysis, and being the main responsible for elaborating the poster. Dr. Marcos Rodrigues has collaborated very closely in the conception of the methodology and in the review of the poster design. Dr. Juan de la Riva has also participated on reviewing the results.

Jiménez-Ruano A, Rodrigues M, Jolly W M, de la Riva Fernández J. (2018). Assessing the influence of fire weather danger indexes on fire frequency and burned area in mainland Spain. ***Geophysical Research Abstracts*** (Oral presentation). Vol. 20, EGU2018-13196, Vienna, Austria.

In this work, the PdD student, Adrián Jiménez Ruano, is responsible for most of the work, having carried out the statistical and spatial analysis, and being the main responsible for preparing the presentation. Dr. Marcos Rodrigues and Dr. Juan de la Riva have collaborated very closely in the conception of the methodology and in the review of the oral communication. Dr. Matt Jolly has also contributed to the calculation of fire weather indices calculation as well as to the review of the results.

Jiménez-Ruano A, Rodrigues M, Jolly W M, de la Riva Fernández J. (2018). The role of drought and magnitude in the temporal evolution of fire occurrence and burned area size in mainland Spain. ***Geophysical Research Abstracts*** (Poster contribution). Vol. 20, EGU2018-13520, Vienna, Austria.

In this work, the PdD student, Adrián Jiménez Ruano, is responsible for most of the work, having carried out the statistical and spatial analysis, and being the main responsible for elaborating the poster. Dr. Marcos Rodrigues and Dr. Juan de la Riva have collaborated very closely in the conception of the methodology and in the review of the poster. Dr. Matt Jolly has also contributed to the methodology design as well as to the review of the results.

La presente tesis doctoral se ha elaborado siguiendo la modalidad de compendio de publicaciones. El doctorando, Adrián Jiménez Ruano, figura como primer autor y responsable de casi todos los artículos. Seguidamente 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:

Jiménez-Ruano A, Rodrigues M, de la Riva J (2017) Understanding wildfires in mainland Spain. A comprehensive analysis of fire regime features in a climate-human context. ***Applied Geography*** 89:100-111. https://doi.org/10.1016/j.apgeog.2017.10.007

Factor de impacto JCR: 3,117 (1er cuartil, "Geography").

En este trabajo el doctorando, Adrián Jiménez Ruano, es responsable de la mayor parte del trabajo, desarrollando gran parte del análisis estadístico y espacial, siendo el responsable último de la redacción de los contenidos. El Dr. Marcos Rodrigues Mimbrero ha colaborado en el desarrollo de algunas tareas y también ayudó en el proceso de escritura. Tanto el Dr. Juan de la Riva and Marcos Rodrigues Mimbrero figuran como coautores en calidad de directores de tesis, siendo responsables del tema general de la investigación y habiendo colaborado en la revisión de los resultados.

Jiménez-Ruano A, Rodrigues M, de la Riva J (2017) Exploring spatial–temporal dynamics of fire regime features in mainland Spain. ***Natural Hazards and Earth System Sciences*** 17:1697-1711. https://doi.org/10.5194/nhess-17-1697-2017

Factor de impacto JCR: 2,281 (2º cuartil, "Geosciences, Multidisciplinary").

En este trabajo el doctorando, Adrián Jiménez Ruano, es el responsable de la mayor parte del trabajo, desarrollando gran parte del análisis estadístico y espacial, siendo el responsable último de la redacción de los contenidos. El Dr. Marcos Rodrigues Mimbrero y el Dr. Juan de la Riva también han colaborado muy estrechamente en la revisión de la metodología y los resultados.

Jiménez-Ruano A, Rodrigues M, Jolly W.M, de la Riva J (2019) The role of short-term weather conditions in temporal dynamics of fire regime features in mainland Spain. ***Journal of Environmental Management*** 241:575-586. https://doi.org/10.1016/j.jenvman.2018.09.107

Factor de Impacto JCR: 4,865 (1er cuartil, "Environmental Sciences").

En este trabajo el doctorando, Adrián Jiménez Ruano, es el responsable de la mayor parte del trabajo, desarrollando gran parte del análisis estadístico y espacial, siendo el responsable último de la redacción de los contenidos. El Dr. Matt Jolly figura como coautor por su colaboración en la construcción de parte de la metodología y revisión de los resultados preliminares siendo además el responsable de la estancia en la que se desarrolló la investigación. El Dr. Marcos Rodrigues Mimbrero y el Dr. Juan de la Riva también han colaborado muy estrechamente en la revisión de los resultados.

Rodrigues M, **Jiménez-Ruano A**, de la Riva J. (2016) Analysis of recent spatial–temporal evolution of human driving factors of wildfires in Spain. ***Natural Hazards*** 84(3):2049-2070. https://doi.org/10.1007/s11069-016-2533-4

Factor de impacto JCR: 1,833 (2º cuartil, "Geosciences, Multidisciplinary").

En este trabajo, el Dr. Marcos Rodrigues es responsable de la mayor parte del trabajo, habiendo realizado el análisis estadístico y espacial, y siendo el principal responsable de la redacción de todos los contenidos. El doctorando Adrián Jiménez Ruano ha colaborado en la ejecución de parte de la metodología. El Dr. Juan de la Riva es el responsable del tema general de la investigación y ha colaborado en la revisión de los resultados.

Rodrigues M, **Jiménez-Ruano A**, Peña-Angulo D, de la Riva J. (2018) A comprehensive spatial-temporal analysis of driving factors of human-caused wildfires in Spain using Geographically Weighted Logistic Regression. ***Journal of Environmental Management*** 225: 177-192. https://doi.org/10.1016/J.JENVMAN.2018.07.098

Factor de impacto JCR: 4,865 (1º cuartil, "Environmental Sciences").

En este trabajo, el Dr. Marcos Rodrigues es responsable de la mayor parte del trabajo, habiendo realizado el análisis estadístico y espacial, y siendo el principal responsable de la redacción de todos los contenidos. El doctorando, Adrián Jiménez Ruano, ha colaborado en la realización de parte de la metodología y parte de la cartografía del trabajo final. La Dr. Peña-Angulo ha proporcionado los datos climáticos empleados en la investigación. El Dr. Juan de la Riva es el responsable del tema general de la investigación y ha colaborado en la revisión de los resultados.

Además, se han incluido otros trabajos en el cuerpo de la investigación, pero que aún no han sido publicados:

Rodrigues M, **Jiménez-Ruano A**, de la Riva J (En revisión). Fire regime dynamics in mainland Spain. Part 1: drivers of change. ***Science of the Total Environment.***

Factor de impacto JCR: 5,589 (1º cuartil, "Environmental Sciences").

En este trabajo el Dr. Marcos Rodrigues Mimbrero, es el responsable de la mayor parte del trabajo, desarrollando gran parte del análisis estadístico y especial, siendo el responsable último de la redacción de los contenidos. El doctorando, Adrián Jiménez Ruano, ha colaborado muy estrechamente en la confección del proceso metodológico y en obtener parte de los resultados, y el Dr. Juan de la Riva también ha participado activamente en la revisión de los resultados.

Jiménez-Ruano A, de la Riva J, Rodrigues M (En revisión). Fire regime dynamics in mainland Spain. Part 2: a near-future prospective of fire activity. ***Science of the Total Environment.***

Factor de impacto JCR: 5,589 (1º cuartil, "Environmental Sciences")

En este trabajo el doctorando, Adrián Jiménez Ruano, es el responsable de la mayor parte del trabajo, desarrollando gran parte del análisis estadístico y espacial, siendo el responsable último la redacción de los contenidos. El Dr. Marcos Rodrigues Mimbrero ha colaborado muy estrechamente en la confección del proceso metodológico final y revisión del texto, y el Dr. Juan de la Riva también ha participado estrechamente en la revisión de los resultados.

Por último, se han incluido varias contribuciones de congresos en dos apéndices específicos:

Apéndice D

Jiménez-Ruano A, Rodrigues M, de la Riva Fernández J. 2018. Identifying pyroregions by means of Self Organizing Maps and hierarchical clustering algorithms in mainland Spain, in: Viegas, D.X. (Ed.), ***Advances in Forest Fire Research*** (VIII International Conference on Forest Fire Research). Imprensa da Universidade de Coimbra, Coimbra, pp. 495–505. https://doi.org/https://doi.org/10.14195/978-989-26-16-506_54

En este trabajo, el doctorando Adrián Jiménez Ruano es el responsable de la mayor parte del trabajo, habiendo realizado el análisis estadístico y espacial, y siendo el principal responsable de la redacción de todos los contenidos. El Dr. Marcos Rodrigues ha colaborado muy estrechamente en la preparación del proceso metodológico y en la revisión de la redacción. El Dr. Juan de la Riva también ha participado estrechamente en la revisión de los resultados.

Apéndice E

Jiménez-Ruano A, Rodrigues M, de la Riva Fernández J. (2017). An analysis of wildfire frequency and burned area relationships with human pressure and climate gradients in the context of fire regime. ***Geophysical Research Abstracts*** (Poster contribution). Vol. 19 EGU2017-15084, Vienna, Austria.

En este trabajo, el doctorando, Adrián Jiménez Ruano, es el responsable de la mayor parte del trabajo, habiendo realizado el análisis estadístico y espacial, y siendo el principal responsable de la elaboración del póster. El Dr. Marcos Rodrigues ha colaborado muy estrechamente en la concepción de la metodología y en la revisión del diseño del póster. El Dr. Juan de la Riva también ha participado en la revisión de los resultados.

Jiménez-Ruano A, Rodrigues M, de la Riva Fernández J. (2017). Assessing the influence of small fires on trends in fire regime features at mainland Spain. ***Geophysical Research Abstracts*** (Poster contribution). Vol. 19, EGU2017-15755, Vienna, Austria.

En este trabajo, el doctorando, Adrián Jiménez Ruano, es el responsable de la mayor parte del trabajo, habiendo realizado el análisis estadístico y espacial, y siendo el principal responsable de la elaboración del póster. El Dr. Marcos Rodrigues ha colaborado muy estrechamente en la concepción de la metodología y en la revisión del diseño del póster. El Dr. Juan de la Riva también ha participado en la revisión de los resultados.

Jiménez-Ruano A, Rodrigues M, Jolly W M, de la Riva Fernández J. (2018). Assessing the influence of fire weather danger indexes on fire frequency and burned area in mainland Spain. ***Geophysical Research Abstracts*** (Oral presentation). Vol. 20, EGU2018-13196, Vienna, Austria.

En este trabajo, el doctorando, Adrián Jiménez Ruano, es el responsable de la mayor parte del trabajo, habiendo realizado el análisis estadístico y espacial, y siendo el principal responsable de la preparación de la presentación. El Dr. Marcos Rodrigues y el Dr. Juan de la Riva han colaborado muy estrechamente en la concepción de la metodología y en la revisión de la comunicación oral. El Dr. Matt Jolly también ha contribuido al cálculo de los índices meteorológicos de incendios, así como a la revisión de los resultados.

Jiménez-Ruano A, Rodrigues M, Jolly W M, de la Riva Fernández J. (2018). The role of drought and magnitude in the temporal evolution of fire occurrence and burned area size in mainland Spain. ***Geophysical Research Abstracts*** (Poster contribution). Vol. 20, EGU2018-13520, Vienna, Austria.

En este trabajo, el doctorando, Adrián Jiménez Ruano, es el responsable de la mayor parte del trabajo, habiendo realizado el análisis estadístico y espacial, y siendo el principal responsable de la elaboración del póster. El Dr. Marcos Rodrigues y el Dr. Juan de la Riva han colaborado muy estrechamente en la concepción de la metodología y en la revisión del póster. El Dr. Matt Jolly también ha contribuido al diseño de la metodología, así como a la revisión de los resultados.

ABSTRACT

Fire has always been an intrinsic feature in various ecosystems around the world. In environments heavily populated by humans, their actions have altered these natural fire regimes for others that are fundamentally anthropogenic in nature. In the context of Mediterranean Europe, the number of forest fires and their observed burnt area fell into a general decline during the late twentieth century, which led to a reduced incidence of fire in most Mediterranean ecosystems historically affected by recurrent fires. Therefore, the change in past fire regimes is evident, mainly due to human intervention instigating a very demanding policy of total exclusion of fire.

However, the recent evolution of fire regimes presents a high spatial and temporal variability. On the other hand, future scenarios predict a growing impact of the human factor (more land abandonment, poor management of forests and adhering exclusively to suppression methods), which will result in increased fire activity due to a greater amount of available fuel. In addition, climatic conditions are expected to cause increasingly larger burned areas (higher temperatures, more frequent heat waves and droughts), which will undoubtedly have a negative effect on both ecosystems and future societies.

All these factors make an adequate zoning of fire regimes necessary from a spatial-temporal perspective, which allows the relationship between the altered fire regime and associated socio-economic and environmental factors to be determined, as well as detecting temporal trends in regions with decreasing activity, or on the contrary, an increase in the incidence of fires. Therefore, finding these areas will lead to improved management and prevention of forest fires.

This doctoral dissertation focuses on enriching knowledge for identifying and interpreting homogeneous regions of fire regimes. A wide range of methods of statistical analysis and spatial modeling are employed. The dissertation is structured according to the following objectives: Objective 1 focuses on analyzing the spatial-temporal distribution of the main features defining the fire regime during the recent period. Objective 2 aims to further describe the influence of meteorological danger on the evolution of fire activity. Objective 3 evaluates the change in the relative contribution of anthropogenic factors on forest fires. Objective 4 focuses on explaining the evolution and causes of changes or transitions in fire regimes during the recent (1974-2015) and future (2016-2036) periods. Finally, Objective 5 centers on the transfer of the zoning of fire regime typologies into an integral mapping of pyroregions

The results indicate that fire regimes in mainland Spain have undergone several changes, mainly a considerable decrease in fire activity in most of the territory, although it still remains high in the north (especially in winter). The diverse machine-learning methods employed, especially Random Forest, have demonstrated their potential in terms of revealing the fire drivers behind fire regime evolution. Moreover, forecasting by the ARIMA model has confirmed the ongoing tendency towards a lower incidence of fire. All indications are that preventive measures should take greater prominence in areas with an abrupt decrease in wildfires, as they are significantly more prone to large ones in the short and medium term.

RESUMEN

El fuego ha coexistido de forma intrínseca en diversos ecosistemas a nivel global. En el caso de los ambientes más humanizados la acción del hombre ha alterado esos regímenes de incendio naturales por uno fundamentalmente de carácter antrópico. En el contexto de la Europa Mediterránea, el número de incendios forestales y su área quemada observados han experimentado un descenso general durante el final del siglo XX. Esto ha supuesto un declive de la incidencia del fuego en la mayoría de los ecosistemas mediterráneos históricamente afectados por incendios recurrentes. Por tanto, es evidente la alteración de los regímenes de incendio pasados, debido principalmente a la intervención humana con una política de exclusión total del fuego muy exigente.

No obstante, la evolución reciente de los regímenes de incendio presenta una alta variabilidad espacial y temporal. Por otro lado, las perspectivas de futuro vaticinan un impacto creciente del factor humano (abandono del campo, gestión de los bosques y mantenimiento de la supresión excluyente), lo que consecuentemente derivará una mayor actividad de incendios debido a una mayor cantidad de combustible disponible. Asimismo, se prevén unas condiciones climáticas cada vez más propensas a generar incendios de gran superficie (mayores valores de temperatura, mayor frecuencia de olas de calor y sequías), lo que sin duda afectará negativamente tanto a los ecosistemas como las sociedades futuras.

Todos estos factores hacen necesaria una adecuada zonificación de los regímenes de incendio desde una perspectiva espacio-temporal, la cual permita conocer la relación existente entre el régimen de incendios alterado y los factores socio-económicos y ambientales asociados. Así como detectar tendencias en el tiempo en regiones que experimenten un descenso de la actividad, o, por el contrario, incremento de la incidencia de incendios. Por tanto, conociendo estas zonas se podrá mejorar la gestión y prevención contra incendios forestales.

Esta tesis doctoral se enfoca en enriquecer el conocimiento sobre la identificación e interpretación de regiones homogéneas de regímenes de incendio. Para ello se recurre a un amplio abanico de métodos de análisis estadísticos y de modelado espacial. La tesis se estructura de acuerdo a los siguientes objetivos: el objetivo 1 se centra en analizar la distribución espacio-temporal de las principales métricas que definen el régimen de incendio durante el periodo reciente. El objetivo 2 pretende profundizar en la influencia del riesgo meteorológico en la evolución de la actividad de los incendios. El objetivo 3 evalúa el cambio de la contribución relativa de los factores antropogénicos en los incendios forestales. El objetivo 4 se enfoca en explicar la evolución y causas de los cambios o transiciones de los regímenes de incendios durante el periodo reciente (1974-2015) y futuro (2016-2036). Finalmente, el objetivo 5 pone la atención en la traslación de la zonificación de tipologías de regímenes de incendios hacia una cartografía integral de piroregiones.

Los resultados indican que los regímenes de incendio en la España peninsular han experimentado diversos cambios, principalmente una disminución considerable de la actividad de incendios en la mayor parte del territorio, aunque todavía persiste una alta actividad en el extremo norte (especialmente en invierno). Los diversos métodos de aprendizaje automático empleados, especialmente *Random Forest*, han demostrado su potencial en términos de revelar los factores que impulsan la evolución del régimen de incendios. Además, la proyección ARIMA ha confirmado la tendencia actual hacia una menor incidencia de incendios. Todo apunta a que las medidas preventivas deben tomar más protagonismo en áreas con un abrupto descenso de la ocurrencia, ya que son significativamente más propensas a grandes incendios a corto y medio plazo.

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CHAPTER 1: INTRODUCTION

This chapter presents the state of the art of the fire phenomenon and the relevance of the fire regime term, summarizing the range of methods applied in the fire regime modelling and introduce the conceptually differences between the fire regime and pyroregion terms.

1.1. The wildfire phenomenon

Fire plays an important role in the processes governing the Earth System (Bodí et al., 2012), and are a natural mechanism in plant succession, which has been shaping the distribution and dynamics of many vegetation species during millennia. Forest fires were originally a natural hazard, but can become a major disturbance when its frequency and/or intensity is altered (De Santis and Chuvieco, 2009), causing major environmental and socioeconomic impacts. These alterations can be classified into two main groups depending on the time elapsed after the fire event: short-term and long-term.

In general, the immediate or short-term consequences of forest fires usually have a negative impact on the environment. Among the most significant ecological repercussions are : soil erosion (Pérez-Cabello et al., 2006; Shakesby, 2011), physical-chemical alterations in the surface horizons of the soil (Badía et al., 2014; González-Pérez et al., 2004), disappearance of species and degradation (Pérez Cabello et al., 2010), loss of biodiversity (Durán-Medraño et al., 2017), and carbon emissions (Raupach et al., 2007). In the Mediterranean region, the heavy autumn rains commonly occurring after summer wildfires cause the onset of water erosion- channeled or laminar – which usually transfer organic matter and nutrients to the soil but reduce its structural stability (Bodí et al., 2012). In their last stage, they help to form rills, wash fines and increase stoniness.

However, in the mid-to-long-term (months or years post-fire) a high percentage of burned areas and vegetation usually make a recovery. The degree of this process will depend on many factors: climate/weather conditions before and after the fire event (Davis et al., 2019; Dimitrakopoulos et al., 2011), the strategies of the main species - seeders vs resprouters (Díaz-Delgado et al., 2003), the interval of fire recurrence (Juli G. Pausas and Vallejo, 1999), the various alterations on the soil (Certini, 2005), as well as restoration treatments and human intervention (logging, forestry management, etc.), which have contributed to mitigating or worsening post-fire conditions (Shakesby, 2011). In this respect, in many developed countries, the abandonment of agricultural activities in rural areas (Vélez, 2004; Whitlock, 2004) has increased the amount and continuity of fuel load, which will promote more virulent and extensive fires (megafires) in the coming years. On the other hand, in developing countries, the situation is quite different, even with great spatial variability, there is an overall intensification of tropical plantations and the persistence of the traditional use of fire for land clearing and shifting cultivation (Le Page et al., 2010).

Globally, a decrease both in burned area and fire-related emissions is reported reaching a historical minimum in 2013 (Arora and Melton, 2018; Van Der Werf et al., 2017). One of the major causes of this tendency is related to the so-called fire exclusion policy often implemented in developed countries (Minnich, 1983). However, there is a high level of variability between large-scale regions. For instance, both Southeast Asia and North America show an increasing trend in burned area (Doerr and Santin, 2016). With the former, this trend is due to an intensification of crop burning, and there is a clear influence of climate change in the latter (Earl and Simmonds, 2018), where the number of fires has decreased, which means fewer fires but affecting a larger area. In Mediterranean Europe, the risk from forest fires is expected to increase, which will require much stronger advanced management (IPCC, 2014). Although many studies show different trends depending on the regions, the statistics show a general decline in fire frequency and burned area (Turco et al., 2016), although in certain regions within Portugal, Greece and Spain some authors found significant increases in fire activity during the period 1985-2009 (Marcos Rodrigues et al., 2013). Recently, there has been a slight upturn in fire activity, especially in regions with infrequent fires and little danger (such as Scandinavia), in 2018 when numerous fires exceeded extinguishing capacity (Martin Ruiz de Gordejuela and Puglisi, 2018).

In the particular case of mainland Spain, forest fires are the greatest alteration to ecosystems, as it is one of the countries in the Mediterranean region with highest frequency of fire events and annual cumulative burned forests (Darques, 2016). According to the Spanish Ministry of Agriculture and Environment (MAGRAMA), over the period 2008-2017, an annual average of 12,573 fires were reported, affecting a mean area of 101,411 ha. The European Fire Database (EFFIS) shows that Portugal is in first place, with an average of 18,204 fires per year for the same period, although with a slightly smaller average affected area (91.160 ha). Since the 1960s, an increase in the number of disturbances has been detected, probably due to improved detection and data collection systems. In fact, this trend has currently been strongest during the winter fire season, partially induced by human activities (Moreno et al., 2014) and also related to the lengthening of the fire season (Jolly et al., 2015). In addition, the yearly frequency has increased in the majority of regions, except on the Mediterranean coast (Turco et al., 2016) where recent socioeconomic changes have promoted more hazardous landscapes coupled with warmer climate conditions. The trend is similar for burned areas, with a significant decrease since the mid-1990s (Marcos Rodrigues et al., 2013; San-Miguel-Ayanz et al., 2013; Urbieta et al., 2019). This can be explained by improved methods of extinguishing fires. On the other hand, an overall decrease in the frequency of large fires has also been reported (A. Cardil and Molina, 2013), along with the fact that these particular events cause the greatest environmental and social damage, as well as having become difficult to predict and control in the worst fire-weather conditions of recent years (Regos et al., 2014).

All this points towards the existence of changes in fire regimes, which will lead to probable implicit differences between different regions and different transitions (from activity regression, stability, to activity progression). Given the diversity of fire features and driving factors involved in these changes, the study of the characteristics and temporal evolution of fire regimes in mainland Spain should address the fact that not only must it focus on these two metrics (fire frequency and burnt surface), but also try to capture the wide diversity of parameters concerning forest fires. In addition, it is important for the analysis to include the contribution from the main driving factors, both natural and anthropogenic. In this way, there will be a greater depth of knowledge on future and foreseeable trends of fire regimes.

It is evident, therefore, that the study of fire regimes is a promising and crucial research line to better understand the occurrence of wildfires. However, assessing fire regime is complex, due to the continuous spatial-temporal changes they have experienced. It is important to remember that natural fire regimes defined pre-industrial landscapes, until altered by human intervention (Syphard et al., 2007), often exceeding thresholds of fire resilience in ecosystems (Stevens-Rumann et al., 2018). On the other hand, some authors have observed a transition towards a more significant role of climate factors in recent fire regimes (Pechony and Shindell, 2010), resulting in a greater probability of ignition and propagation (Thompson et al., 2011). In Spain, the main changes are related first with anthropogenic pressure over wildlands, and later with climate-weather conditions (Pausas and Fernández-Muñoz, 2012). In fact, fire regimes have been strongly related to climatic conditions after the 1970s, pointing out that forest fires are caused mostly by fuel and droughts. In addition, the structure of fuel and the landscape is shaping the current fire regime-climate relationship (Pausas and Paula, 2012). However, most of these studies usually focus solely on the number of fires and burned area, which highlights the lack of an analysis of the evolution of the fire regime based on additional features such as cause, seasonality and the role of large fires.

1.2. The concept of fire regime: definitions and components

The birth of the concept of "fire regime" dates from the 1820s, with a group of French-speaking botanists and agronomists in African colonies (Krebs et al., 2010). In the United States, the concept was not adopted until the early 1960s, when the idea of fire as a natural disturbance shaping ecosystems was incorporated. The current definitions of this term are based on a selection of variables that are questionable because it implies a certain degree of subjectivity. For this reason, there is still no consensus on the definition of the concept of "fire regime", which varies largely according to the research objectives (Krebs et al., 2010), the scale of analysis and available data. Chuvieco (2009) termed fire regime as "the average fire conditions within a particular area persistent over a long period of time". Some authors advocate the inclusion of spatial-temporal patterns of fire activity, as well as the type of fuel burned, as an ecological proxy (Gill, 1973). Hence, it seems clear that the notion of fire regime is somehow 'variable' and susceptible to including different features and dimensions. In fact, it is widely believed that fire regime features have been and continue to change dramatically in time and space(Morgan et al., 2001a). However, there are several common features usually accepted (Pyne, 2001). Among the wide variety of fire regime features found the literature, fire frequency, fire size distribution, intensity, seasonality and mean annual burned area are the most frequently used in fire regime assessments (Archibald et al., 2013). Recent papers in mainland Spain dealing with fire regimes, such as those by Moreno and Chuvieco (2016, 2013), have contributed significantly to shaping the first geographical delimitations of the fire regime, although they still assumed fire features to be stationary over time.

In this PhD dissertation, fire regime is defined as "the average behavior of a set of key fire features (fire frequency, burned area, large fires, winter frequency and natural fires), persistent over space and time". However, the proposed approach goes one-step further, including not only fire regime characteristics but also their trends, and the factors influencing their potential variability in space and time. It is important to note, that the degree of participation of fire regime components and driving factors is variable and will depend on the scale of the study, the time period examined and the minimum spatial unit of reference. For instance, in the case of the size of the study region, the role of climatic factors will have a smaller or larger range of variability, depending on the differences between the altitude gradients. On the other hand, the period studied will allow a more robust analysis of trends in both fire metrics and driving factors, provided it is over a longer time range. Finally, the size of the spatial unit influences the level of detail with which the variable in question is spatialized, analyzed and represented.

1.3. Methodological approaches in fire regime modelling

The study of the fire regime was conducted using a wide variety of factors and approaches. In the first place, it is important to differentiate the two major governing forces: climate and human activities. The first refers to variables such the lack of precipitation events (droughts), as well as the prevailing thermal regime during the fire season that controls the probability of ignition, fire size and seasonality, thus shaping the patterns of large-scale fire regimes (Boulanger et al., 2013). The second aspect, human causality has a double face, since it can impact the occurrence positively or negatively, depending on the level of influence (Syphard et al., 2007). In this respect, the active suppression of forest fires may reduce their activity, while at the same time, humans cause ignitions in the vicinity of infrastructures (primary and secondary road networks) or in the wildland-urban interface.

The capacity of current methodologies for space-time modeling of forest fire frequency and burned area is evident. Among others, the methods employed vary from the use of bivariate and multiple regression, as in the examples of DaCamara et al. (2014) and Syphard et al. (2007), through the analysis of specific spatial patterns (Fuentes-Santos et al., 2013; Liu et al., 2012), probabilistic models (Silvestrini et al., 2011), machine learning such as Random Forest (Boulanger et al., 2013), multivariate adaptive regressions splines – MARS (Boulanger et al., 2014) and maximum entropy (Duane et al., 2015). Another branch of research has used specific-devoted simulation models, as change points (Mouillot et al., 2002) or power law (Malamud, 1998; Malamud et al., 2005; Perera and Cui, 2010). In Spain, several articles suggest that alterations in fire regimes have been driven by climate, land use changes and suppression policies (Moreno et al., 2014) as well as different propagation patterns in Catalonia (Duane et al., 2015).

The majority of studies have used regression models in combination with simulated data from general climate models (GCM) (Boulanger et al. 2013; DaCamara et al. 2014; Kilpeläinen et al. 2010; Krawchuk et al. 2009; Pechony and Shindell 2010; Terrier et al. 2014; Westerling et al. 2011) based on IPPCC projections of future emission scenarios or Regional Climate Models (RCM). Most of these studies envisage an increasing burned area in regions such as Portugal (DaCamara et al., 2014), California (Westerling et al., 2011) and the Iberian Peninsula (Sousa et al., 2015). However, several authors point out different trends depending on the regions of the world (Krawchuk et al., 2009; Pechony and Shindell, 2010), including showing opposite tendencies with increasing frequency and a slight decline of burned area in the Northeast of Spain (Turco et al., 2014).

In the fire-climate framework, many authors have analyzed the relationship between climate change and shifts in certain characteristics of fire regimes (fire frequency, surface area, seasonality, average fire range, maximum fire size, etc.) in many regions. For example, in the boreal forests of North America (Kasischke and Turetsky, 2006) they resort to historical records, the analysis of individual years by categories of eco-zones and the start time of individual events. In Canada, the Fire Growth Model has been used to model the risk of lightning and human-induced ignitions (Nitschke and Innes, 2013). On the other hand, most of the studies have assumed future projections with similar environmental and anthropic conditions to the current ones (Boulanger et al., 2014, 2012), thus showing certain limitations in trend detection since they assume a "static" of non-climate conditions for the future. Therefore, the growing importance of estimating the present and future impact of climate change on fire regime has become a key issue in risk assessment and adaptation strategies, emerging as the cornerstone in national and international climate programs (Turco et al., 2014), such as the European project FUME (2010-2013).

However, it is well-known that the democratic and massive use of future climate change scenarios implies a high degree of uncertainty. In other words, the most complicated issue is the validation of projected data, especially those by GGM or RCM models, as there is still no time series with which to correlate. This is why some authors leaned towards the "safest" alternatives, such as the auto-regression and moving average models (ARIMA). ARIMA models are known for their good performance in fields such as markets and the economy (Loi and Ng, 2018; Matyjaszek et al., 2019), as well as in the environmental framework: vegetation (REF) or climate change. In the context of forest fire, Preisler and Westerling (2007) employed ARIMA using temperature forecasting to assess fire danger in western USA, whereas, Boubeta et al. (2016) applied a simplified version of ARIMA (ARMA) without the integrated component in order to predict burnt area in Galicia. The main virtue of ARIMA models lies in the fact that they predict future trends and seasonality, with the historical time series of data as their only reference. As a result, the principle of parsimony is guaranteed in the model, since the minimum number of variables is used, being more easily reproducible and without creating an over adjustment.

When discussing the use of spatial modeling methods and the prediction of forest fire characteristics in specific areas, a wide repertoire of methodological approaches and explanatory variables can be brought to bear. The scale of analysis (global, regional or local), the proposed objectives and the nature of the data used will condition the analysis framework. Among the most widely applied models to date, GLM and GAM (Generalized Linear Models and General Additive Models, respectively) stand out as flexible generalizations of linear regression, able to deal with non-normal distributions of the variable under study (fire activity) or the explanatory variables (climate, weather, topography, population, wildland urban-agricultural interfaces, road network, etc.). This modeling framework is adequate, since forest fire data usually depict non-linear response functions. In addition, Geographically Weighted Regression (GWR) is a more advanced alternative that has also been applied in the context of wildfires (Koutsias et al., 2010; Sá et al., 2011), whose main advantage is that it allows the calculation of local regression parameters, useful for analyzing the spatial behavior of each explanatory variable and determining their level of significance. The few works conducted in mainland Spain point to a certain degree of spatial variability (Martínez-Fernández et al., 2013), confirming that human driving factors vary over both space and time(Rodrigues et al., 2016) and are losing explanatory power in favor of climatic conditions (Rodrigues et al., 2018).

Another important aspect when estimating the probability of the occurrence of wildfires is to analyze the characteristic of fuels and how they interact with climatic variables (precipitation, temperature, wind, relative humidity, etc.). The role of forest fuels not only largely determines the likelihood of ignition, but also the speed of propagation, and ultimately the severity. In this respect, numerous fire weather danger indices have been used to relate meteorological data to fire (Fire Weather Index: FWI, Standardized Precipitation-Evapotranspiration Index: SPEI, Palmer Drought Index: PDSI, among others). Some studies carried out in Portugal (Fernandes et al., 2014) stressed the positive relationship between fire and weather together with fuel hazard and the final burned area. In eastern-Spain, (Cardil et al., 2019) pointed out the importance of a multi-temporal perspective when studying the link between drought and burned area for different vegetation communities. In any case, that there is a strong influence from the flammability of the fuel and its spatial continuity on fire frequency and burned area has been demonstrated by fuel model classifications (Prometheus, NFFL, NFDRS, McArthur, FBP - see Arroyo, Pascual, and Manzanera (2008) for more details.

1.4. Fire regime vs pyroregion

Because of the potential usefulness and interest in predicting how the behavior of fire regimes evolves, this PhD Thesis aims to optimize the identification and characterization of fire regimes in mainland Spain, beginning with the identification of the most relevant features of fire, and continuing by evaluating the direction and extent of regional trends both in space and time. Until now, most works focused on broad-scale fire regime modeling based on large ecological and administrative units. In Canada, the next step was to outline homogeneous fire regime (HFR) zones without this traditional approach, since it does not capture the spatial heterogeneity of fire regimes and could lead to spatially inaccurate estimations of future fire activity (Boulanger et al., 2014). In Spain, only a few papers have defined fire regime units but by attributing a static image in their delimitation (Moreno and Chuvieco, 2013), i.e., not incorporating the non-stationary behavior of fire features. To overcome this limitation, our goal is to provide a projection of the possible future evolution of these homogeneous fire regime zones, since until now the few projects carried out in the Iberian Peninsula have focused on only forecasting selected components, such as the affected surface (Sousa et al., 2015).

Generally, the spatial delimitation of fire regimes is based exclusively on the consideration of the main, defining features of fire. However, this zoning has to be incorporated into a more comprehensive spatial context that also integrates the driving factors (both climatic and human) most directly related to forest fires. In this respect, the first study that put forward this new concept was Fréjaville & Curt (2015), which added the concept of "pyroclimates" to the wildfire literature. They developed a new framework for analyzing regional changes in fire regimes from specific spatial-temporal patterns of forest fires and climate, defining it as a geographical entity displaying homogenous attributes with respect to fire regime, climate conditions (bioclimatic variables and fire danger indices) and the temporal trends of both. Therefore, we adopted part of the innovation of this concept in our term "pyroregions", but in our case, we added human factors into the definition and not only the climate conditions. As result, we define pyroregion as "a geographical area sharing homogeneous fire regime features, climate-human conditions and the evolution of both".

To sum up, the main difference between "fire regime" and "pyroregion" lies fundamentally in the nature of their underlying factors. In the case of fire regime, it broadly refers to the average conditions in terms of fire features over time and space. The pyroregion transcends fire regime being a geographical entity that characterizes by uniform or homogeneous fire activity, but is also influenced by self-defining climatic and human conditions.

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CHAPTER 2: OBJECTIVES AND RESEARCH DESIGN

This chapter summarizes the objectives and structure of the thesis, connecting the former with their corresponding publications and appendices that compose the whole research.

The **working hypothesis** of this PhD Thesis is **that mainland Spain presents different fire regimes defined by specific** fire frequency, burned area, seasonality and cause, which are non-stationary over **space and time**, thus **allowing modeling and envisaging their evolution**. To understand the complexity of the phenomenon, we had to investigate the driving forces of fire regimes, which ultimately would lead to the definition of dynamic **pyroregions**, thus improving fire management, prevention and preparedness within a context of climate and socio-economic change.

Therefore, the **main objective of this research was to translate** the variety of homogenous zones of **fire regimes into pyroregions**, providing insights into **their possible evolution** through the **identification and characterization of their main components** (frequency, size, seasonality, cause, etc.) and **driving factors** (climate, weather, human pressure, etc.).

2.1. Research questions

In order to address the main objective stated before, five **specific research questions** (RQs) or **objectives** were formulated and addressed by studying several research papers. Table 1 shows the correlation between each specific objective and its corresponding publications.

RQ 1: What is the spatial-temporal distribution of the main fire regime features and what is its relationships with climate-human factors?
1st Objective: Explore the spatial-temporal distribution of fire regime features and their relation with climate-human factors.

RQ 2: What role does fire-weather danger play in the temporal evolution of fire regime features?
2nd Objective: Estimate the contribution of fire-weather danger on the observed evolution of fire activity.

RQ 3: What have been the spatial-temporal changes in the influence of human factors on wildfires?
3rd Objective: Analysis spatial-temporal changes in the role of anthropogenic drivers on wildfires.

RQ 4: What changes have been experienced by fire regimes and which factors are behind these dynamics?
4th Objective: Characterize the dynamics of recent-future fire regimes and know the drivers of their changes.

RQ 5: How are pyroregions distributed in space on the basis of the observed evolution of fire regime typologies and drivers?
5th Objective: Translate the fire regime typologies scheme into pyroregions.

Table 1. Summary of the specific objectives and their corresponding publication or contribution.

Objective	Publication
1st **Objective:** Explore the spatial-temporal distribution of fire regime features and their relation with climate-human factors.	**CHAPTER 5** ***-Jiménez-Ruano A,*** *Rodrigues M, de la Riva J (2017) Understanding wildfires in mainland Spain. A comprehensive analysis of fire regime features in a climate-human context. Applied Geography 89:100-111.* https://doi.org/10.1016/j.apgeog.2017.10.007 ***-Jiménez-Ruano A****, Rodrigues M, de la Riva J (2017) Exploring spatial–temporal dynamics of fire regime features in mainland Spain. Natural Hazards and Earth System Sciences 17:1697-1711.* https://doi.org/10.5194/nhess-17-1697-2017 **APPENDIX A** -Supplementary material from "*Understanding wildfires in mainland Spain. A comprehensive analysis of fire regime features in a climate-human context*". **APPENDIX E** -***Jiménez-Ruano A****, Rodrigues M, de la Riva Fernández J. (2017). An analysis of wildfire frequency and burned area relationships with human pressure and climate gradients in the context of fire regime. Geophysical Research Abstracts (Poster contribution). Vol. 19 EGU2017-15084, Vienna, Austria.* -***Jiménez-Ruano A****, Rodrigues M, de la Riva Fernández J. (2017). Assessing the influence of small fires on trends in fire regime features at mainland Spain. Geophysical Research Abstracts (Poster contribution). Vol. 19, EGU2017-15755, Vienna, Austria.*
2nd **Objective:** Estimate the contribution of fire-weather danger on the temporal evolution of fire activity.	**CHAPTER 6** ***-Jiménez-Ruano A****, Rodrigues M, Jolly W.M, de la Riva J (In Press) The role of short-term weather conditions in temporal dynamics of fire regime features in mainland Spain. Journal of Environmental Management 17:1697-1711.* https://doi.org/10.1016/j.jenvman.2018.09.107 **APPENDIX B** -Supplementary material from: "*The role of short-term weather conditions in temporal dynamics of fire regime features in mainland Spain*" **APPENDIX E** ***- Jiménez-Ruano A****, Rodrigues M, Jolly W M, de la Riva Fernández J. (2018). Assessing the influence of fire weather danger indexes on fire frequency and burned area in mainland Spain. Geophysical Research Abstracts (Oral presentation). Vol. 20, EGU2018-13196, Vienna, Austria.* ***- Jiménez-Ruano A****, Rodrigues M, Jolly W M, de la Riva Fernández J. (2018). The role of drought and magnitude in the temporal evolution of fire occurrence and burned area size in mainland Spain. Geophysical Research Abstracts (Poster contribution). Vol. 20, EGU2018-13520, Vienna, Austria.*
3rd **Objective:** Analysis of spatial-temporal changes in the role of anthropogenic drivers on wildfires.	**CHAPTER 7** *-Rodrigues M,* ***Jiménez-Ruano A****, de la Riva J. (2016) Analysis of recent spatial–temporal evolution of human driving factors of wildfires in Spain. Natural Hazards 84(3):2049-2070.* https://doi.org/10.1007/s11069-016-2533-4 *-Rodrigues M,* ***Jiménez-Ruano A****, Peña-Angulo D, de la Riva J. (2018) A comprehensive spatial-temporal analysis of driving factors of human-caused wildfires in Spain using Geographically*

	Weighted Logistic Regression. Journal of Environmental Management 225: 177-192. https://doi.org/10.1016/J.JENVMAN.2018.07.098
4th Objective: Characterize the dynamics of recent-future fire regimes and know the drivers of their changes.	**CHAPTER 8** -*Rodrigues M,* ***Jiménez-Ruano A****, de la Riva J. (In press). Fire regime dynamics in mainland in Spain. Part 1: drivers of change. Science of the Total Environment.* ***-Jiménez-Ruano A****, de la Riva J, Rodrigues M. (In press). Fire regime dynamics in mainland Spain. Part 2: a near-future prospective of fire activity. Science of the Total Environment.* **APPENDIX C** -Supplementary material from: "*Fire regime dynamics in mainland in Spain. Part 1: drivers of change. Science of the Total Environment*".
5th Objective: Translate the fire regime typologies scheme into pyroregions.	**CHAPTER 9** ***-Jiménez-Ruano A****, Rodrigues M, de la Riva J. (to be submitted) Mapping recent pyroregions on the basis of spatial-temporal patterns of fire regimes and environmental-human datasets in mainland Spain* **APPENDIX D** ***-Jiménez-Ruano A,*** *Rodrigues M, de la Riva J. (2018) Identifying pyroregions by means of Self Organizing Maps and hierarchical clustering algorithms in mainland Spain. in: Viegas, D.X. (Ed.), Advances in Forest Fire Research (VIII International Conference on Forest Fire Research). Imprensa da Universidade de Coimbra, Coimbra, pp. 495–505. https://doi.org/https://doi.org/10.14195/978-989-26-16-506_54*

2.2. Research structure

The contents of the Thesis are organized as follows: Chapter 3 presents a description of the study area. Chapter 4 summarizes the data sources and methods employed in the research, complementing the information already published. Chapters 5 to 8 bring together the original version of accepted and published articles. Lastly, the last two chapters (Chapter 9 and 10) portray the final outline of pyroregions and summarize the main conclusions, respectively. Figure 1 summarizes the main databases and methodologies employed in the investigation according to the first four specific objectives.

In addition, a complementary section provides further information, organized into five appendixes (A, B, C, D and E). The first three correspond to the supplementary material in three publications of the main body of this thesis, appendix A belongs to the paper entitled "*Understanding wildfires in mainland Spain. A comprehensive analysis of fire regime features in a climate-human context*", appendix B is part of the article "*The role of short-term weather conditions in temporal dynamics of fire regime features in mainland Spain*" and appendix C corresponds to the manuscript under review *"Fire regime dynamics in mainland Spain. Part 1: drivers of change"*. Appendix D refers to Chapter 3 of the book "*Advances in Forest Fire Research*" edited by Domingos Xavier Viegas, as a result of the contribution in the *"VIII International Conference on Forest Fire Research"*, held in the city of Coimbra (Portugal) from 9 to 16 November 2018. The latter appendix includes several abstracts from different conference contributions held in EGU 2017 and EGU 2018.

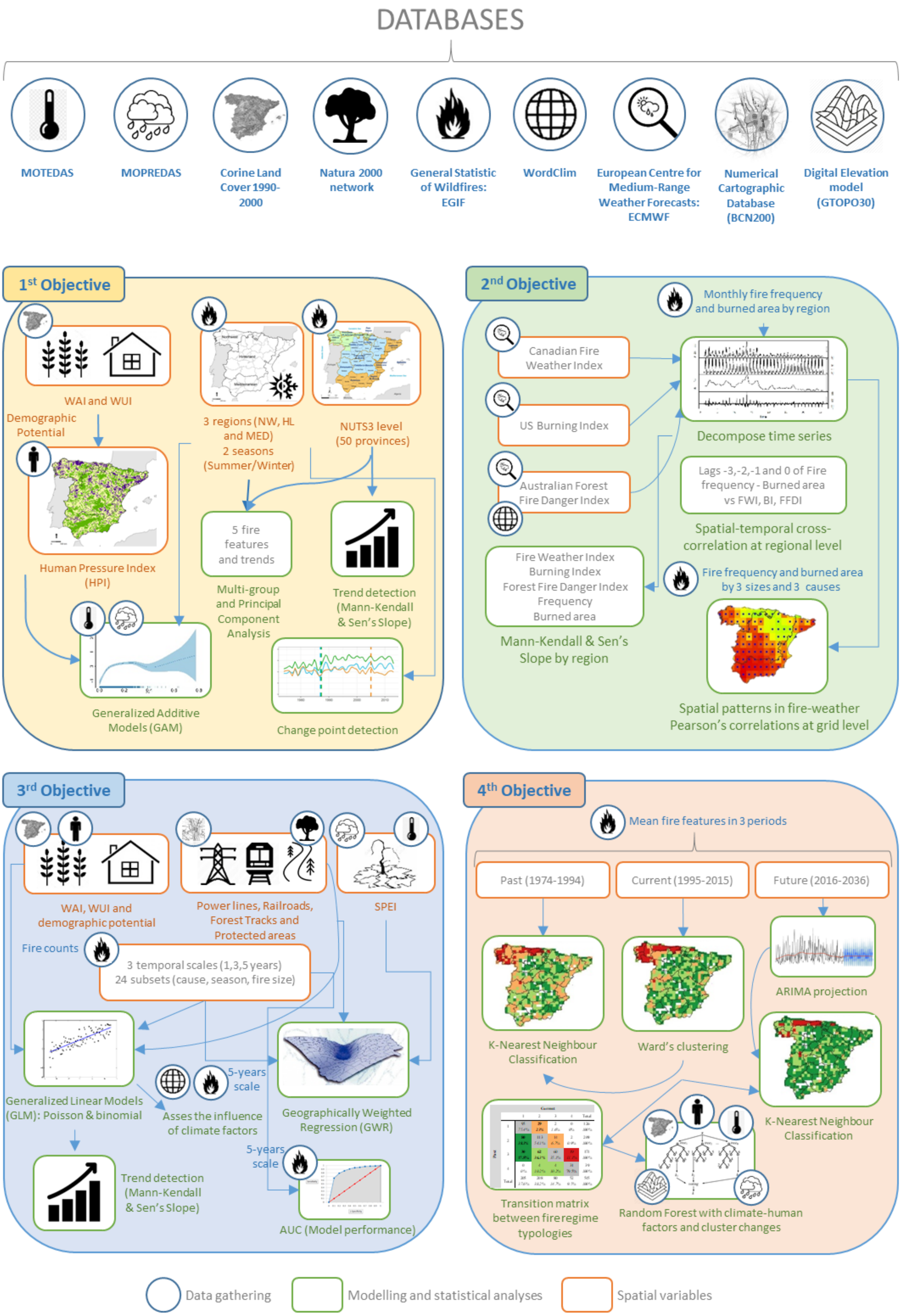

Figure 1 Conceptual workflow of the thesis according to the first four specific objectives.

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CHAPTER 3: STUDY AREA

This chapter presents a description of the study area where the thesis has had its spatial framework.

The study area encompasses the whole of mainland Spain (excluding the Balearic and Canary archipelagos and the autonomous cities of Ceuta and Melilla) and covers a total surface area of 498,000 km^2. Spain is very biophysically diverse, presenting a wide variety of climatic, topographical and vegetation communities. This diversity also appears when discussing socioeconomic conditions in terms of settlement systems and population structure, production sector, changes in land use and land cover, or structure of the territory.

From a biogeographical point of view, mainland Spain is dominated by two different bioregions. The Eurosiberian, located in the northwestern area, and the Mediterranean, covering the remaining territory. The Eurosiberian is characterized by an Oceanic climate (according to the Spanish Climate Atlas - AEMET 2011- and based on the Köppen-Geiger's climate classification - *Cfb*) distinguished by milder temperatures throughout the year and high precipitation evenly distributed across the year (average values over 1,000 mm) peaking during winter. This area is mostly covered by various types of vegetation from deciduous oak (*Quercus robur, Fraxinus excelsior* or *Fagus sylvatica*) and ash to evergreen oak woodlands. However, this region is also heavily dominated by forest plantations such as *Pinus radiata* and *Eucalyptus globulus*. In turn, the Mediterranean region is characterized by hot-summers in almost 40% of the territory (*Csa*) and cold semi-arid (*BSk*) climateswith high annual thermal amplitude and precipitation irregularly distributed over the year (peaking in autumn and spring, with a clear minimum during summer). Therefore, there are notably drier and warmer conditions than the Eurosiberian region, especially across the southeastern region and the Ebro Valley. These conditions, coupled to human activity, favors complex mosaics of agricultural systems and plant communities. Sclerophyllous and evergreen vegetation, such as *Quercus ilex*, *Quercus suber* and thermophilous scrublands (maquis and garrigue formations), dominate the region, and forest areas mainly consist of pines (*Pinus halepensis*, *Pinus sylvestris*, *Pinus nigra*, *Pinus pinea* or *Pinus pinaster*). Furthermore, bioclimatic (altitudinal) belts exist within each region in mountain areas such as the Pyrenees along the French border or the Sierra Nevada on the southern Mediterranean coast. These sub-regions host a large variety of tree species that are common in central Europe.

Human activity also changes its footprint across the region. According to Corine Land Cover 2006 (CLC 2016), in the northwest area, approximately 68% of the region is covered by forests, shrubs or grassland. This land cover has been traditionally shaped by seasonal grazing (agricultural burning to maintain pastures and grasslands) at the end of the winter. In the hinterland region, there has been a gradual abandonment of agricultural activity (crops and pastures) meaning that around 54% of its territory is covered by wildland. Meanwhile, the Mediterranean region, the most populated area, has the lowest proportion of woodland (roughly 22%) because of an extended wildland-urban interface caused by the expansion of urban and tourism developments during the last few decades (Moreno et al., 2014)

The Spanish population is currently around 47,007,367 inhabitants according to 2019 INE provisional data and therefore, the fifth most populated country in the EU, behind Germany, France, the United Kingdom and Italy, according to Eurostat 2018 (European Union Statistics). The distribution of the population is characterized by the sharp contrast between the hinterland and coastlines, with the highest density located mainly along the Mediterranean corridor, and also in some coastal areas in the north. The remaining inland regions have a lower demographic density, except the Madrid area.

Spain has a diversity of agricultural landscapes closely related by climatic conditions. In the northwest, the main type of cropland is a mosaic of cereals interspersed with patches of forest (mainly Eucalyptus plantations). In the hinterlands, most of the territory is occupied by the so-called Mediterranean trilogy (i.e. extensive cereal, olives and vineyards) with few wildlands. In the western hinterland, the *dehesa* is the predominant agroforest landscape. Finally, in the Mediterranean corridor, apart from the Mediterranean trilogy, intensive fruit farms are commonly found, which also dominate the banks of the main rivers (Ebro, Guadalquivir, Guadiana, Tajo and Duero). According to Delgado-Serrano and Hurtado-Martos (2018), who analyzed the CLC changes between 1987-2011, the major expansion in land use was in olive groves and irrigated land. On the contrary, the largest reduction was found in complex crop mosaics, in addition to mixed zones (natural vegetation-crops).Due to the variety of landscapes, climate and socioeconomic conditions, three different regions - Northwest (NW), Hinterland (HL) and Mediterranean (MED) – were outlined (Figure 2), following the criteria established by the Spanish Environmental Ministry in their annual fire reports (MAGRAMA, 2012, 2007, 2002).

Figure 2. Spatial distribution of the three regions (Northwest, Hinterland and Mediterranean), NUTS3 and NUTS2 administrative units in mainland Spain.

Administratively, the NW region includes the autonomous communities of Galicia, Asturias, Cantabria and the Basque Country, as well as the provinces of León and Zamora. This region is located within the Eurosiberian region, excluding the Pyrenees. The HL region includes all of the autonomous communities without a coastline, except for the provinces of León and Zamora (included in the NW region). This region is located in the transition boundary between the Mediterranean and Eurosiberian regions, thus sharing characteristics in terms of climate influence and plant species. Finally, the MED region, situated completely within the Mediterranean biogeographical area, includes all the autonomous communities along the Mediterranean coast, as well as the western provinces of Andalusia.

These regions exhibit homogeneous areas in terms of wildfire activity and seasonal averages by merging entire provinces or autonomous communities and have been previously used in other recent works like Moreno et al. (2014) as they are expected to have self-defining fire regimes. The spatial coverage of these regions is similar to other zoning proposals from authors such as Sousa et al. (2015) or Trigo et al. (2016) that are also based on NUTS3 aggregations, although they include Portugal as well. In terms of fire occurrence, the number of winter fires is noticeably high (35.7%), especially in the Northwest region. In turn, burned area caused by lightning represents a low fraction of the total amount (around 6.5%) and it is usually concentrated in mountain areas (mainly in the provinces of León-Zamora and the Iberian Range). Generally, the spatial distribution of fires is characterized by the heavy concentration of fire activity in the northwest, but also in the Mediterranean corridor, and inner mountain ranges. In terms of inter-annual distribution, mainland Spain features two distinct peaks of fire activity. The first during the summer months, which affects the whole territory, but with a significant incidence in the hinterlands and the Mediterranean region. The second occurs during late winter- early spring and is located mainly in the northwest. On the other hand, the evolution of the main fire features throughout the study period can be summarized as an increase in generalized activity up to a peak in the mid-1990s, since when there has been a gradual decrease in both frequency and burned area (Figure 3).

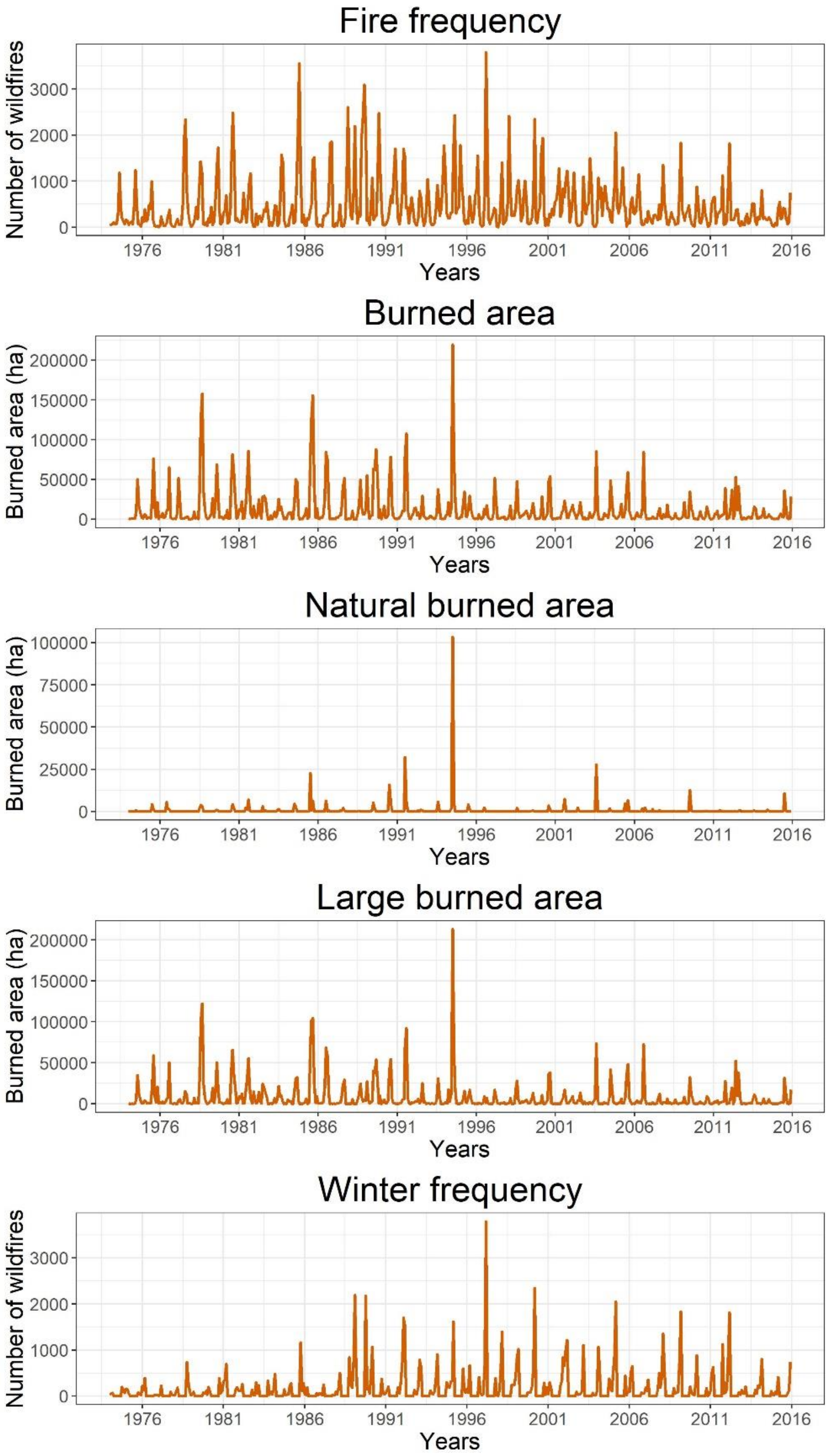

Figure 3. Temporal evolution of the main fire features in the period 1974-2015.

4

CHAPTER 4: MATERIALS AND METHODS

This chapter describes in detail all data and methods employed to conduct this thesis. The research has been addressed at three different spatial scales: regional, provincial (NUTS-3) and local (grid or cell). In addition, the fire features have been adapted depending on the objective proposed and/or the availably of the explanatory variables.

4.1. Datasets and sources

4.1.1. The Spanish fire database

The General Statistics of Wildfires (Estadística General de Incendios Forestales: EGIF) database stands out for its precision and completeness, being one of the oldest wildfire databases in Europe, beginning in 1968 (Moreno et al., 2011; Vélez, 2001). Its inception coincided with the adoption in the same year of Law 81/1968 on Forest Fires, the first legal mandate expressly designed to address a serious problem. by means of prevention and control actions (López Santalla et al., 2017). The Bureau of Defense Against Forest Fires (Área de Defensa Contra Incendios Forestales: ADCIF) is the institution responsible for standardizing, maintaining, drafting and publishing these statistics, based on the information submitted by autonomous communities for every fire occurring in the country. All the baseline information collected is organized in different sections in the Spanish Forest Fire Reports (Parte de Incendio Forestal: PIF), which currently collects more than 150 data fields for each fire. It should be noted that this structure, sections and type of information gathered has varied over the years, undergoing a total of eight modifications from its first publication.

Systematic collection of statistical data on forest fires began in 1956. Until then they were collected manually and on an irregular basis by the provincial services. In 1967, the Calculation Office of the Institute of Forestry Research and Experiences acquired a computer, which enabled a new model of PIF to be created that came into operation in the second semester of that year. Therefore, the first Annual Forest Fire Report was published in 1968, but included data on fires that had occurred since 1961. With regard to the quality of the data, it should be noted that, in the early years, it only included fires that affected forest masses or large non-forest areas, although subsequently, the rest of the fires were taken into account, even those of less than 1 ha.

The spatialization of information has changed over the years from its beginning, when the minimum spatial unit of reference was the province (NUTS3), with a 10 x 10 km reference grid adopted after 1974. Until 1979, only those fires occurring in public and reforestation forests were recorded. Later, in the period 1980-1988, all fire events were collected, regardless of ownership. Since 1982, the municipality was added as a field in each fire location. Later, in 1989-1992, the PIF was reformed to incorporate important fields such as time, use of air, means or motivations related to intentionality. Since 1990, the General Statistic has been submitted to the European Commission for integration into the Community database EFFIS (European Forest Fire Information System).

On the other hand, the traditional demarcation by region employed in the annual fire reports was the same for the period 1968-1977 with a total 7 regions (excluding the Balearic and Canary Islands): Galicia, North, Northeast, Ebro, Levante, the Hinterland and Andalusia. Since 1978, the number of regions increased to 10 (excluding the Canary Islands): Galicia, North or Cantabric (Asturias and Cantabria), Ebro (Aragón), Northeast (Catalonia-Baleares), Duero (Castilla-León), Center (Castilla–La Mancha), Levante (Valencia-Murcia), Extremadura, West Andalusia and East Andalusia. Moreover, from 1982 a more extensive section referring to weather conditions throughout the particular year was added, provided by the National Institute of Meteorology. From 1983, the previous regions were replaced by the Autonomous Communities. The sections of the current PIF contain the following common information:

a) **Location data:** Includes the ID of the fire (IDPIF) as 10 digits. The codes of the autonomous community, province, municipality containing the fire ignition point (created in 1983), tile and grid (created in 1974) and UTM coordinates.

b) Time data: Day, month, year, hour and minutes when the fire was detected, but also first arrival of engines by land (created in 1988), first arrival of fire-fighting aircraft (created in 1989), first airborne brigade arrival (created in 2005), and time when the fire was controlled and extinguished.
c) Detection: Who first detected the fire (permanent guard, forestry officer, aircraft, etc.) and place of origin (road, path, house, train rail, crops, etc.).
d) Ignition causes: Differences between known and supposed cause (since 1998), lightning, negligence and accidental causes, arson (created in 1989), unknown cause, rekindled fire (since 1998), identification or otherwise of the person causing it, and type of day (festival, Saturday, festival eve and working day).
e) Danger conditions when the fire starts: Meteorological data (days from last rain, maximum temperature, relative humidity, wind) fuel model (since 1989) and probability of ignition.
f) Type of fire: Surface, crown or subsoil (since 1989).
g) Fire suppression media: Type of land transport (vehicles, helicopters), number of different personnel (technical staff, forestry agents, professional firefighters, civil staff, army, etc.) and extinguishing methods (aircrafts, helicopters, retardants, etc.).
h) Fire suppression techniques: Direct or indirect attacks, firewall opening, etc.
i) Losses: People killed and injured, civil protection incidents, type of surface affected, environmental impacts.

4.1.2. Fire data and fire features

Fire features were retrieved from the General Wildfires Statistics (EGIF) database. Generally, fire records for 1974-2015 were selected and spatialized according to the 10 x 10 km UTM reference grid which is used by firefighting crews for approximate locations of fire ignition points. Fire count data, total burned area size, ignition triggering date and fire cause were retrieved for each event. In all cases, only information on fires larger than 1 ha was retained because small fires (i.e. fires with less than 1 ha affected) were not fully compiled until 1988. This is a well-known issue affecting other regions in the Mediterranean, such as Portugal (Pereira et al., 2011). Additionally, it is important to remember that in the autonomous community of Navarre, fire data were only available from 1988. Hence, all the analyses conducted in Navarre were based on a slightly different study period (from 1988 to 2010, 2013 or 2015).

The start year was set as 1974, since it was the first year to use the 10 x 10 km grid. Prior to that time, fire data were only recorded at province level, so grid information was not available. The end year fluctuates depending on the temporal frame of other databases required for different analyses. For the first objective, the end year (2010) was chosen because of the availability of climate data from the MOTEDAS and MOPREDAS datasets (described below). For the second objective, the final year was set at 2013, because the sole input was the EGIF database, and at the time of the research, fire data was only available until then.

As stated in section 1.2., regions were outlined following MAGRAMA specifications. In turn, two fire seasons were defined according to Moreno et al. (2014). Thus, annual data were divided into a spring-summer season (S), from April to September; and an autumn-winter season (W) from October to March. From all available fire data information, several fire regime features were constructed separately for the season, region, NUTS3 and grid level. The final number of fire features changes according to each specific objective (see Table 2).

Table 2. Summary of fire regime features constructed, their description and corresponding time period for each specific objective.

Objective	Fire Feature	Description	Time Period
1st. Explore the spatial-temporal distribution of fire regime features and their relation with climate-human factors	Fire frequency (F)	Total number of fires, regardless of size or ignition source	1974-2010 1974-2013
	Burned area (B)	Total fire affected area, regardless of size or ignition source	
	Number of large fires (N500)	Number of fires above 500 ha burned, regardless of ignition source	
	Burned area from large fires (B500)	Overall affected area from fires above 500 ha, regardless of ignition source	
	Number of natural fires (NL)	Number of fires triggered by lightning	
	Burned area from natural fires (BL)	Overall burned area from fires triggered by lightning	
	Number of human fires (NH)	Number of fires triggered by an anthropogenic source	
	Burned area from human fires (BH)	Overall burned area from fires triggered by an anthropogenic source	
2nd. Estimate the contribution of fire-weather danger on the temporal evolution of fire activity.	Fire frequency (F)	Total number of fires, regardless of size or ignition source	1979-2013
	Burned area (B)	Total fire affected area, regardless of size or ignition source	
3rd. Analysis of spatial-temporal changes in the role of anthropogenic drivers on wildfires.	Fire counts	Number of fires by grid	1988-2010 1988-2013
	Fire presence or absence	Recoded into a binary presence or absence of fire recorded	
	25 subsets of occurrence	Combination of two periods, two seasons, two causes and three fire sizes.	
4th. Characterize the dynamics of recent-future fire regimes and know the drivers of their changes.	Fire frequency (F)	Total number of fires, regardless of size or ignition source	1974-2015
	Burned area (BA)	Total fire affected area, regardless of size or ignition source	
	Burned area from natural fires (BAL)	Overall burned area from fires triggered by lightning	

	Burned area from large fires (BA100)	Overall affected area from fires above 100 ha, regardless of ignition source
	Winter fire frequency (FW)	Number of fires occurred in autumn-winter season, (W) regardless of size or ignition source

In total, the calculation of fire occurrence (a total of 229,068 fires in the period 1974-2015, excluding small fires – i.e. less than 1 ha) was constructed by the method developed by De la Riva et al. (2004). This method consists in spatializing fire data as an input for fire modeling by using a kernel approach to interpolate historic fire observations. In terms of monthly mean and total values of the main fire features, a double annual peak can be found (the highest is usually found in August, with a second one in March, see Table 3). However, the second peak disappears for the area burned by large fires (>100 ha) and those caused by lightning, the latter showing a displacement of the summer peak to July.

Table 3. Summary of monthly mean, standard deviation (sd) and total number of fires and burned area for each fire feature in the period 1974-2015 (small fires less than 1 ha are excluded).

Fire feature	Month	Mean	Sd	Total
Fire frequency	January	0.05	188.33	7,199
	February	0.13	479.82	18,691
	March	**0.24**	754.77	**33,329**
	April	0.12	428.94	17,311
	May	0.06	135.09	7,921
	June	0.07	163.06	9,892
	July	0.17	387.86	24,226
	August	**0.34**	675.74	**47,657**
	September	0.29	808.65	40,296
	October	0.09	398.99	13,160
	November	0.03	103.22	3,979
	December	0.04	167.94	5,407
Burned area	January	2,477.85	3,278.01	104,069.51
	February	6,133.04	8,977.37	257,587.55
	March	**11,321.46**	11,995.31	475,501.25
	April	6,277.16	7,694.76	263,640.90
	May	2,985.79	4,329.85	125,403.29
	June	5,778.87	9,068.18	242,712.68
	July	28,265.16	37,616.06	1,187,136.62
	August	**44,804.75**	34,226.26	1,881,799.50
	September	25,413.33	35,333.18	1,067,360.03
	October	7,011.48	12,163.58	294,482.01
	November	1,865.65	3,731.95	78,357.49
	December	3,024.84	5,501.75	127,043.30
Large burned area (> 100 has)	January	1,004.03	1,775.17	42,169.42
	February	2,349.64	4,567.64	98,684.74
	March	3,859.71	4,371.90	162,107.73

	April	2,623.81	4,282.10	110,199.93
	May	1,520.87	3,105.52	63,876.42
	June	4,033.21	8,588.28	169,394.96
	July	23,179.12	35,556.11	973,523.08
	August	**34,094.29**	27,675.81	**1,431,960.15**
	September	16,189	25,104.63	679,938.17
	October	4,087.58	7,829.04	171,678.17
	November	1,071.2	3,344.38	44,990.17
	December	1,795.32	3,886.1	75,403.49
Natural burned area	January	0.39	1.51	16.50
	February	5.01	22.38	210.30
	March	38.91	226.98	1,634.38
	April	20.30	53.86	852.43
	May	49.33	93.17	2,071.79
	June	593.73	1,194.33	24,936.83
	July	**5,772.42**	16,780.78	**242,441.65**
	August	2,469.47	4,578.96	103,717.77
	September	523.36	1,081.92	21,980.98
	October	16.06	46.77	674.57
	November	5.89	30.26	247.40
	December	0.22	0.76	9.30

On the other hand, several explanatory variables can be taken into account when addressing a fire regime characterization. These are usually divided into two groups: natural and human. In the first case, factors related to environmental conditions were selected to represent the general climate gradients and fire-weather. The second group refers to anthropogenic conditions related with the fire ignition and were chosen on the basis of other previous research (Rodrigues et al 2014).

4.1.3. Climate and weather

Climate data were extracted from MOTEDAS (Monthly Temperature Dataset of Spain) and MOPREDAS (Monthly Precipitation Dataset of Spain) datasets. These databases provide monthly climate information at a spatial resolution of 10 x 10 km. They were constructed from real measurements from the Spanish Meteorological Network of weather stations in the period 1951-2010 (González-Hidalgo et al., 2015, 2011). MOTEDAS and MOPREDAS stand out as one of the most accurate databases in the context of climate data for mainland Spain.

Their development was based on the reconstruction of a meteorological data time series from each weather station in the region. This process includes a quality control, consisting of two steps: suspect data identification and inhomogeneity detection. Firstly, a set of reference series was calculated for each original station by means of a monthly correlation matrix between the candidate series and all the others, and selecting the neighboring series with the highest positive monthly correlation coefficient (mean greater than 0.60 and 0.50, for MOPREDAS and MOTEDAS, respectively) within a critical threshold distance of 25 km (for MOTEDAS) and 50 km (for MOPREDAS). The minimum overlapping period required for the correlation computation was set at 7 years from MOTEDAS and 10 years for MOPREDAS.

To assess the suspect data, authors use both ratio and inter-quartile methods, as well as direct and inverse ratios to avoid the zero effect. On the other hand, for homogeneity analyses they applied a combination of tests: Single Normal Homogeneity Test -SNHT, Bivariate, t-Student and Pettit test. Finally, in order to fill the gaps in the data, the method consists in producing a combination of neighboring series with no overlapping periods.

The final database of MOTEDAS consists of 3,066, and MOPREDAS of 2,670 selected homogenous series without suspect data from the different stations of AEMET (Agencia Estatal de Meteorología). After interpolating the stations' data onto the 10 x 10 km grid cells, using an improved version comprising a combination of two weights: one radial weight with a Gaussian shape, and an angular weight. The radial weight prevents undesired exchange of information between different climatic regions, and between either side of the largest mountain chains. The angular weight avoids undesired overweighting of the areas with the highest station density. The mean number of stations involved in the estimation of each grid is approximately 4 for MOTEDAS and 6 for MOPREDAS.

For the first objective of this dissertation, monthly data on annual average maximum temperature (T - Figure 4) and total precipitation in mm (P - Figure 5) in the period 1974-2010 were extracted and adapted to the fire grid using a nearest neighbor procedure. Both maximum temperature and precipitation were later reclassified into 10 homogeneous (equal interval) categories used to construct climate codes for the later fire features relationship plots.

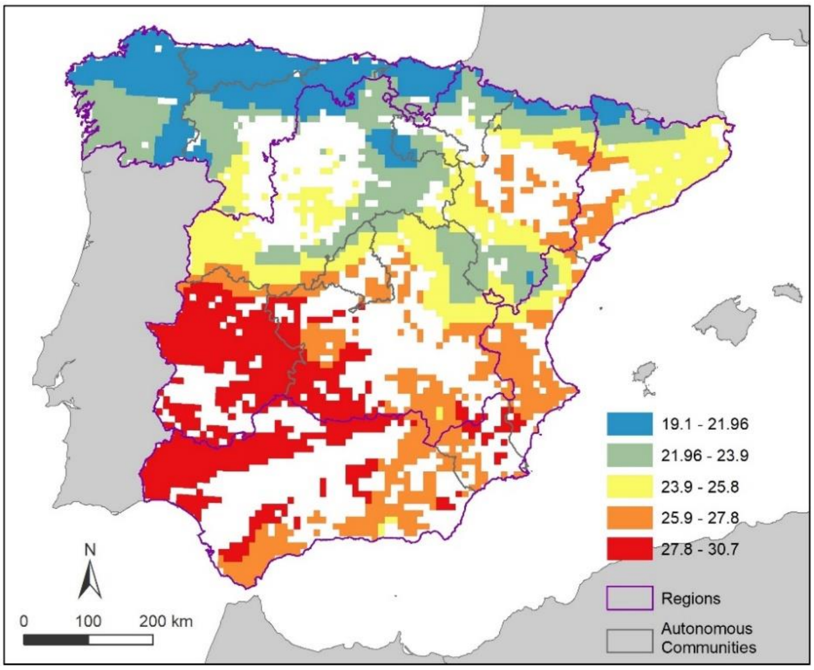

Figure 4. Spatial distribution of average maximum temperature (in ºC) from MOTEDAS.

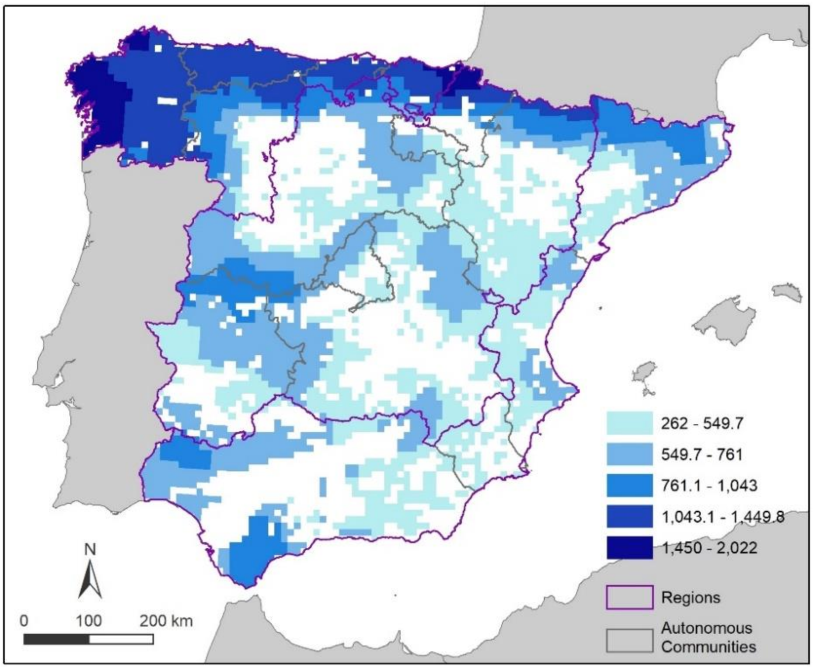

Figure 5. Spatial distribution of total precipitation (in mm) from MOPREDAS.

The ERA-Interim Reanalysis datasets produced by the European Centre for Medium-Range Weather (ECMWF) dataset (Dee et al., 2011) was used to construct three different fire danger indexes (Fire Weather Index: FWI, US Burning Index: BI and Australian McArthur Forest Fire Danger Index: FFDI) necessary to achieve the 2rd objective. The main reason for this choice was due to the fact that this source has a higher spatial and temporal resolution (around 78 km). More specifically, 3-hourly 2 m air temperature, dew point temperature, surface total precipitation, and 10 m wind components were extracted to derive the following climate variables: maximum and minimum temperature, maximum and minimum relative humidity, maximum wind, total daily precipitation amount and total daily precipitation duration (see Jolly 2015 for more details).

The WorldClim database is an interpolate climate surface for global land areas at a spatial resolution of 1 km (Hijmans et al., 2005). Monthly precipitation and mean, minimum, and maximum temperature were included as climate elements, and all input data came from different sources, restricted to all records for the 1950-2000 period. WorldClim was particularly chosen to create the Australian McArthur FFDI, providing the annual mean precipitation data, which when combined with the ECMWF maximum daily precipitation and temperature, produced the Drought Index (see Figure 2 in Chapter 6 and Jolly et al. (2015) for further details on the calculation process). It is therefore part of the achievement of the third objective of this dissertation.

4.1.4. Anthropogenic drivers

The first of the human drivers refers to land use data, and was retrieved from Corine Land Cover 1990 (CLC), since it is centered on the study period. CLC information was used to outline the Wildland-Agricultural Interface (WAI) and the Wildland-Urban Interface (WUI), two variables strongly related to anthropogenic ignitions (V. Leone et al., 2009; Martínez et al., 2004; Rodrigues et al., 2014). WAI represents the length of the boundary between agricultural and wildland areas, and WUI, the length between populated and wildland areas. Both were calculated at fire grid level (Rodrigues et al., 2016).

On the other hand, in order to represent the human pressure over the wildlands, we have chosen the Demographic Potential (DP), which is an aggregate index for the ultimate future potential of the population, was retrieved from (J. L. Calvo and Pueyo, 2008) and based on the following formula:

$$POT_i = \sum_{j=1}^{n} \left(\frac{P_j}{d_{ij}^2} \right) + P_i \qquad (1)$$

where POT_i is the population potential accumulated in cell *i*, P_j are the inhabitants counted in each of the remaining accounting cells of the system and P_i are those of cell *i* itself, while d^2 is the kilometre distance between each pair of cells *i* and *j*.

In the cartographic values of POT_i, those corresponding to its own resident population (P_i) plus those inferred by the *rest* of the system as a consequence of its positioning in the whole are accumulated, obtained by the sum of the population values of *Pj* divided by the distances (*d*) to which each accounting cell (*j*) is divided with respect to (*i*), and the latter elevated to an exponent, which in this case is 2, coinciding with the gravitational formula proposed by Newton.

The demographic potential in 1991 was used at a spatial resolution of 5 x 5 km, later rescaled to the fire grid as the average value inside each cell (Figure 6). WAI, WUI (Figure 7 and Figure 8, respectively) and DP were normalized to a 0-1 interval and then aggregated to develop a Human Pressure Index (HPI, Figure 9), representing the overall pressure of human activities likely to result in fire ignition.

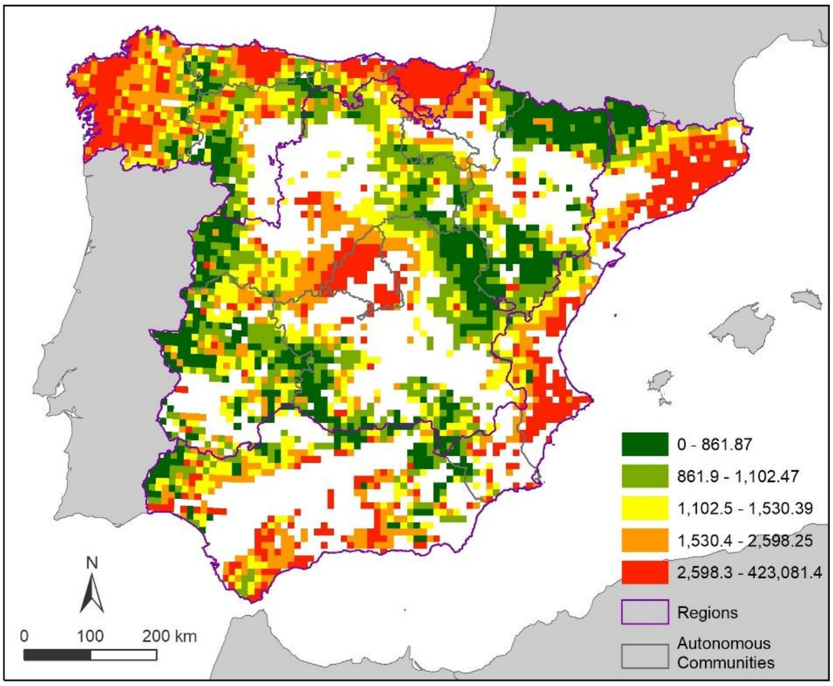

Figure 6. Spatial distribution of the Demographic Potential (DP) in 1991.

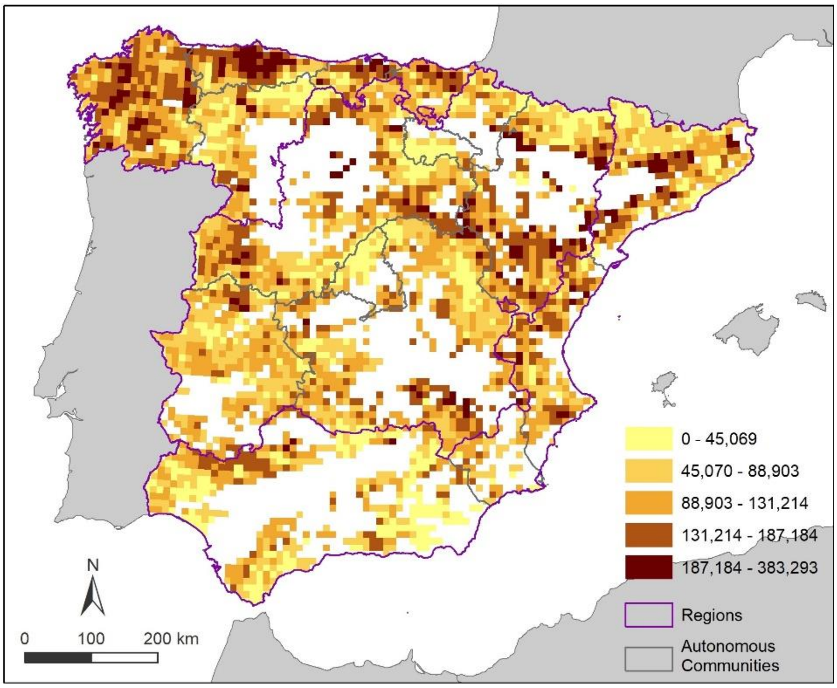

Figure 7. Spatial distribution of the wildland agricultural interface (WAI) length in meters.

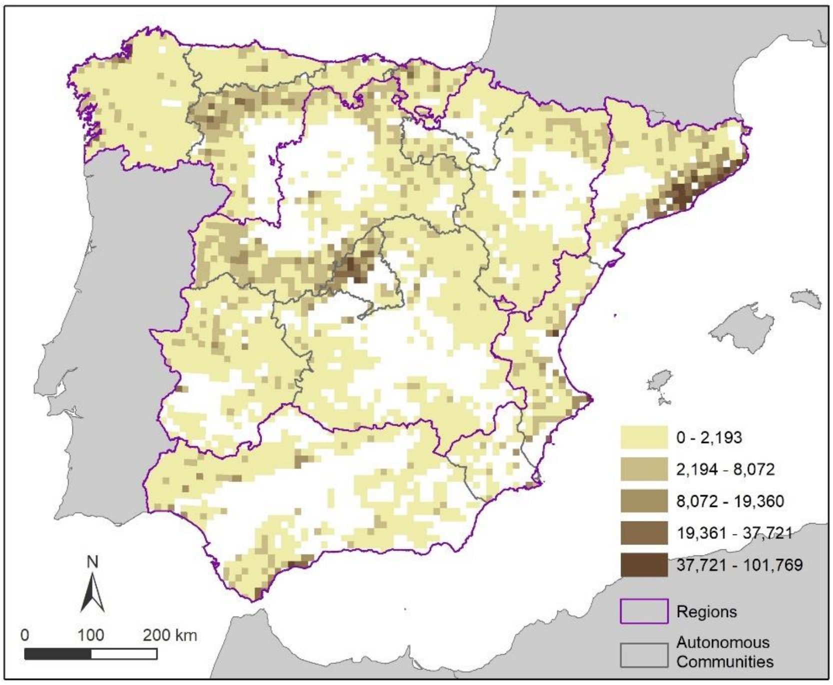

Figure 8. Spatial distribution of the wildland urban interface (WUI) length in meters.

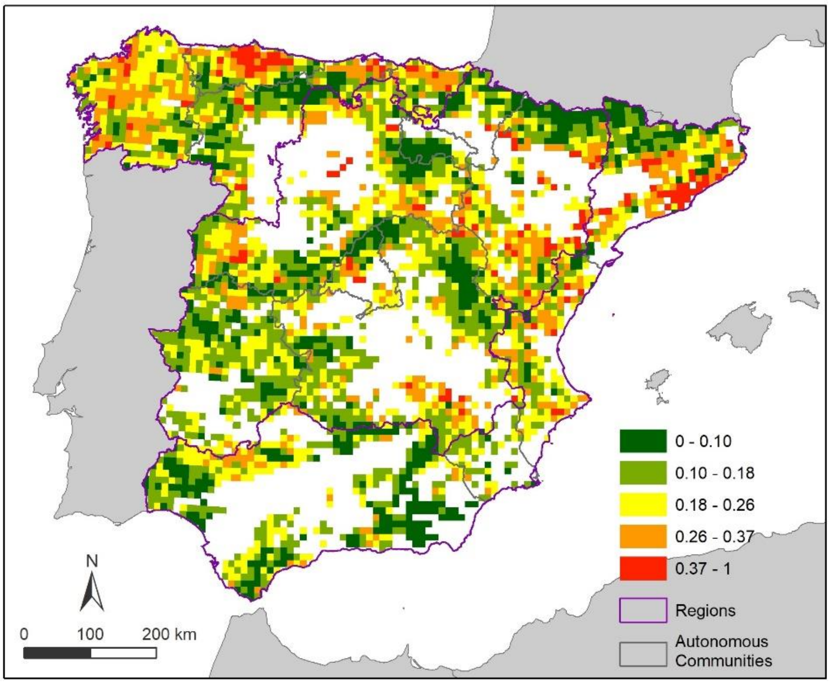

Figure 9. Spatial distribution of the Human Pressure Index (HPI).

Two variables regarding topography were obtained: elevation (Figure 10) and slope (Figure 11). The first, corresponds to the height above sea level in meters and the second, the inclination of the relief in percentages. Both variables were obtained initially from the digital elevation model GTOPO30 at 1 km of spatial resolution, resampled to a 10x10 km grid using the average value of the pixels (both forest and non-forest).

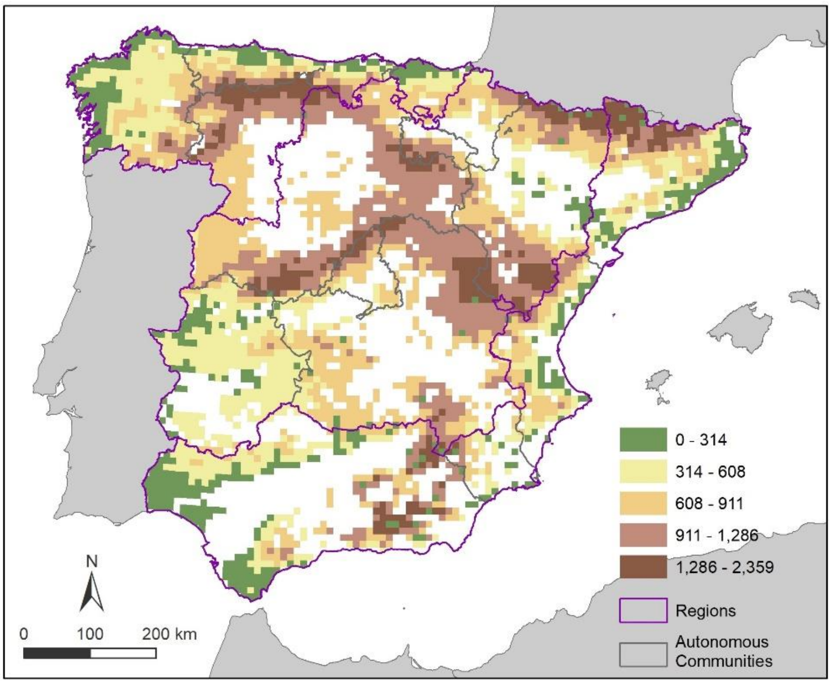

Figure 10. Spatial distribution of mean elevation per grid (in meters).

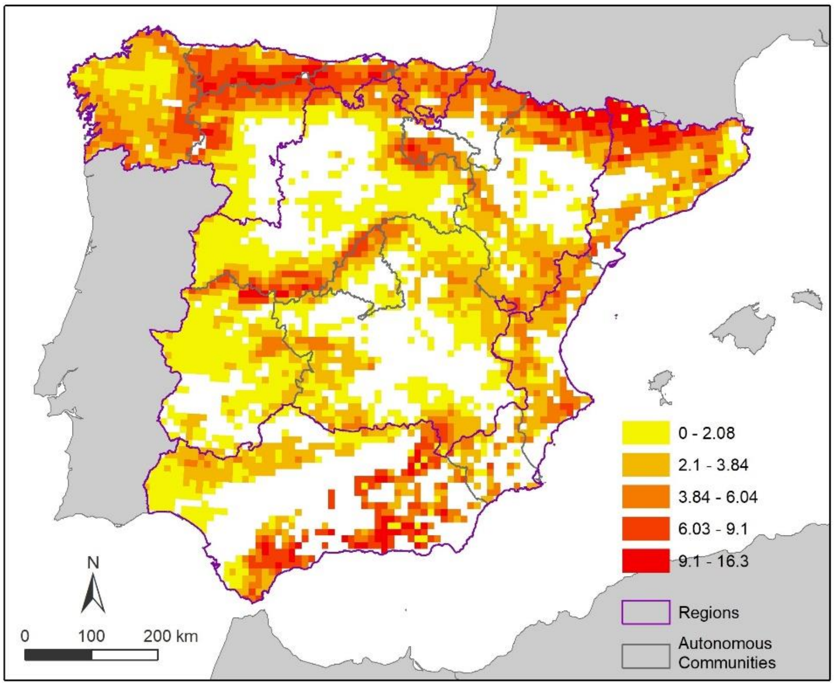

Figure 11. Spatial distribution of the mean slope per grid (in percentage).

4.2. Modelling techniques

In this thesis a wide range of techniques were employed, ranging from those more related to the description and exploration of fire features, to the most advanced, such as trend detection, the classification of fire regimes and regression incorporating driving factors. Therefore, the methodological complexity of the thesis must be emphasized, with almost 20 different methods comprising the body of the research.

4.2.1. Descriptive and explorative

With the first objective of identifying the contribution of fire regime features from each region and season, a Principal Component Analysis (PCA) was carried out. PCA is a classic statistical technique that has been widely used in many research fields, and wildfire modeling is no exception. However, most of the examples of PCA applied to fire science are concerned with synthesizing or reducing the amount of information for regression purposes (Francos et al., 2016; Fréjaville and Curt, 2015; Marcoux et al., 2015; Xu et al., 2006). It is even less common to apply PCA to a fire regime features analysis, even though some examples can be found in Drobyshev, Niklasson, and Linderholm (2012) and Quazi and Ticktin (2016). A PCA estimates the common factors explaining the variance of the input parameters. Initially, variables must be standardized so that each one has mean zero and unit variance, regardless of its scale. This ensures that all variables have the same weight in the analysis (Mardia et al., 1979).

More specifically, a multi-group PCA (MGPCA) procedure, evolved from the classic PCA (Krzanowski, 1984), was implemented. MGPCA can be considered a development of a common principal components analysis (CPCA) of multi-group dataset components analysis proposed by Flury (1984). CPCA is defined as a generalization of PCA to a multi-group setting. This consists in examining the variance-covariance matrices linked to the groups and seeking common orthogonal vectors of loading associated with the components in the groups. However, determination of the common vectors of loadings, which is based on maximum likelihood estimation, leads to a complex algorithm which is time consuming and whose convergence is not guaranteed. MGPCA is simpler and more straightforward than CPCA (Eslami et al., 2013a). MGPCA can deal with the variance-covariance between different groups (in our case regions and seasons). Hence, it is more suitable for group comparison (Eslami et al. 2013a, 2013b) than ordinary PCA. MGPCA was applied by dividing fire data into 6 different groups, one per region (NW, HL and MED) and season (spring-summer and autumn-winter).

The Kaiser Criterion (Kaiser, 1960) was applied to MGPCA outputs, thus retaining only those principal components (PCs) with eigenvalues greater than 1. Following this, a Varimax Rotation (VR) procedure was applied to determine the correlation between input variables (fire regime features) and PCs. VR consists of a PCA coordinates transformation which maximizes the sum of the variance to obtain higher or near-zero coefficients, thus with fewer intermediate values. Consequently, PCA results become easier to interpret (Horst, 1965; Kaiser, 1958). For each PC, the most representative fire regime features were selected, identified and as those with a coefficient furthest from 0. These features were the main contributors to the behavior of fire activity in time (season) and space (region) and thus were key parameters in the definition of fire regimes.

On the other hand, for the first objective, a classic PCA was carried out on Sen's slope values in order to synthetize the changes detected. Furthermore, the temporal behavior was retrieved from PCs on an additional map (see Figure 5, Chapter 5, page 67). Eigenvalues from PCs 1 and 2 were classified into four categories according to their sign (positive or negative trends) and significance level (above (significant) or below (non-significant)) a 90% confidence interval. PCs 3 and 4 were only shown when significant. In this way, homogenous areas according to the observed temporal evolution were outlined.

Correlation

Cross-correlation (CC) is a standard method that estimates the degree of similarity between two discrete time sequences (*x* and *y*) as a function of the displacement (lagged or the delay in synchrony of two temporal events) of one relative to the other (Venables and Ripley, 2002). The CC determined the extent to which weather controls the temporal evolution of the main fire regime features, more specifically, the intra-annual (seasonal) fluctuations of fire activity. To answer this question, CC was conducted at a regional level using the seasonal component from STL. The formula (4 and 5) followed for the definitions of the lags was established by Venables and Ripley (2002) who extended it to several time series observed over the same interval:

$$Y_{\mathrm{ij}}\,(\mathrm{t}) = \mathrm{cov}(\mathrm{X_i}(\mathrm{t}+\mathrm{T}), \mathrm{X_j}(\mathrm{T})) \tag{2}$$

$$\mathrm{C_{ij}}\,(\mathrm{t}) = \frac{1}{\mathrm{n}} \sum_{\mathrm{s}=\max(1,-\mathrm{t})}^{\min(\mathrm{n}-\mathrm{t},\mathrm{n})} [\mathrm{X_i}(\mathrm{s}+1) - \overline{\mathrm{X_i}}][(\mathrm{X_j}(\mathrm{s}) - \overline{\mathrm{X_j}}) \tag{3}$$

where X_i and X_j are the two different time series, t is a particular observation, T is the whole time series, s is the scale estimator, c is the correlation or covariance of these observed pairs. In this case, autocorrelation is not symmetric in *t* for $i \neq j$.

This seeks the association between time series of fire activity (y) in relation to past lags in each fire danger index (x). A set of 4 lags (0, 1, 2 and 3 months) was established as the maximum time window of weather influence.

To identify spatial patterns in fire-weather associations, we applied a correlation analysis at 10x10 km pixel level by means of the Pearson's R correlation coefficient (Best and Roberts, 1975; Hollander and Douglas, 1973). Pearson's R is a parametric statistical test that indicates the extent to which two variables are linearly related. The test requires at least one of the variables to be normally distributed and, in this case, the three fire danger indexes (FWI, BI and FFDI) fulfil this requirement. Pearson's R ranges between +1 and -1, where +1 is perfect positive linear correlation, 0 is no linear correlation, and -1 is negative linear correlation. Pearson's R was calculated and mapped at grid level for each fire-activity subset reporting the R correlation coefficient and its statistical significance ($p < 0.05$). This process was repeated using each weather index.

Multidimensional scatterplots

The visual examination of the relationships between climate/human variables and fire features was considered highly significant. Therefore, multi-dimensional scatterplots (MDS) were used. The construction process is as follows: (i) each grid cell in the study area was coded according to its respective combination of reclassified (from 1 to 10, see Table A1 in Appendix A) temperature and precipitation (henceforth referred to as climate code); (ii) cells were then grouped on the basis of their respective climate code; (iii) fire regime features and Human Pressure Index (HPI) were aggregated as the sum and average value respectively; (iv) multidimensional scatterplots were constructed. Two-dimensional climate space was created on the basis of climate codes for each region and season. On each plane, two additional variables were then plotted. Fire frequency is always represented by proportional circles. Next, another fire regime feature was plotted on the fire frequency circles using different color schemes. This led to multidimensional scatterplots, each one representing four variables (dimensions) in a single plot. Furthermore, in order to explore the relationship between the human pressure index, fire occurrence and climate, additional MDS were constructed representing HPI instead of fire features. HPI was, therefore, only compared to climate and fire frequency, as it mainly linked to fire occurrence.

This kind of analysis proved its potential for identifying relations amongst vegetation, climate and fire in Whitman et al. (2015). However, in this case, a climate space was not included, but two climate gradients (temperature and precipitation) were used instead. The goal was to determine the extent to which fire regimes are controlled by either environmental, human or both factors.

4.2.2. Time series analysis

Change point detection

Change detection or change point recognition aims to identify times when the probability distribution of a time series changes. In order to detect change points in fire features time series four different tests were applied.

- The **Pettitt test** is a non-parametric method commonly applied to detect a single change-point in hydrological or climate series with continuous data (Pettitt, 1979). It tests the H_0 (no change) against the alternative H_1 (a change point exists). One of the advantages of this technique is its robustness to deal with outliers. In the context of wildfire science, the Pettitt test has previously been applied to detect fire regime shifts as a consequence of policy and socioeconomic development in (Pezzatti et al., 2013) and (Moreno et al., 2014).

The Pettitt test is calculated using the following equation:

$$UtT = \sum_{i=1}^{t}\sum_{j=t+1}^{T} \operatorname{sgn}(Xi - Xj) \tag{4}$$

where sgn(X) = 1 for $X > 0$, 0 for $X = 0$ and -1 for $X < 0$, and T is the length of the time series in years. The probability of a significant change existing is calculated as follows:

$$p\ (t) = 1 - \exp\left(\frac{-6\ \cdot U_{t\cdot T}^{2}}{T^{3} + T^{2}}\right) \tag{5}$$

where $|U_{t}, T|$ reaches the maximum value where the most significant change point is found (Pettitt, 1979). This methodology can identify the most probable change point for each fire feature by region and season, in the period examined. A specific function has been developed in R environment to calculate the change point using the Pettitt approach.

As an alternative method to the Pettitt test, three additional algorithms were applied; more specifically, the *cpt.meanvar* function to identify changes in mean and variance, by calculating the optimal positioning of a change point for the input data (Chen and Gupta, 2000):

- **AMOC** (at most one change) method is the simplest expression of the change detection algorithms from the *changepoint* R package v2.2.2. It can detect a single change point (Hinkley, 1970), much the same as the Pettitt test.

- **PELT** (pruned exact linear time) is one of the most widely used methods for change point detection. It can detect multiple change points in large data sets (Killick et al., 2012), unlike the Pettitt test or AMOC. It includes an enhanced optimal partitioning, leading to a substantially more accurate segmentation. This ensures minimum change point detection in a time series, regardless of the applied penalty value. Thus, PELT is known as a more precise algorithm, usually outperforming other methods such as binary segmentation. The CROPS (change points for a range of penalties) penalizing type was selected. The lower the pen.value is, the higher the numbers of change points detected. For this reason, we chose many different minimum pen.values, in order to find at least one, or no more than two, break-points. One of the advantages of this last option avoids continuous false change points commonly found at the beginning/end of the time series (for example, many cases with the AMOC algorithm).

- **BinSeg** (binary segmentation) is an effective method for multiple change point detection (Scott and Knott, 1974). It searches for the first significant change point in a sequence, then breaks the original sequence into two sub-sequences: before and after the first significant change point. The procedure tests the two sub-sequences separately for a change point, with the process repeated until no further sub-sequences have change points (Chen and Wang, 2009). In this case, a possible change point limited in 1 (Q= 1) was previously defined to obtain only the most significant. To this end, the default penalty parameter MBIC (modified Bayes information criterion penalty) was chosen, which has proved effective in reducing overestimation in the number of change points and often detects the correct model (Bogdan et al., 2008). Therefore, there is no need to select a penalty value; hence in all the cases, this value is automatically established as 14.8.

Mann-Kendall and Sen's slope tests

Once the change detection procedures were implemented to determine if and when a certain fire feature has undergone a significant change across the study period, new questions arose: does it imply an increase or decrease in the values of that feature? Moreover, how strong is that change? Is the change stationary or does it vary over space? To answer all these questions, a combination of Mann-Kendall (MK) and Sen's Slope (SS) tests were used.

MK is a non-parametric statistical test appropriate for identifying trends in time series of data (Kendall, 1975; Mann, 1945). It is suitable 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 non-existence and existence of a trend in the time series of the observational data, respectively. Previous studies by San-Miguel-Ayanz et al. (2012) and Rodrigues et al. (2013) support the use of MK in the context of wildfire science. MK main outputs are the τ value and its associated significance level (p value). τ can be used to determine the sign of the trend, i.e. upward ($\tau > 0$) or downward ($\tau < 0$). Trends are considered significant when p-value < 0.05. To facilitate the interpretation of MK outcomes, an aggregated parameter was calculated combining the τ and p value, the so-called "signed p-value". It combines information on both sign and significance, calculated as the multiplication of the significance level either by 1 when $\tau > 0$ or by -1 when $\tau < 0$.

The magnitude of the change was subsequently assessed by means of the SS (Sen, 1968), a non-parametric alternative for estimating the median slope joining all possible pairs of observations, which enables a comparison of the magnitude of the detected trends. Both MK and SS were calculated for all fire features by region and NUTS3 level and for both seasons.

Seasonal-Trend Decomposition

In order to address the relationship between time series of fire activity (overall fire frequency and burned area) and weather, indices were decomposed using Seasonal-Trend Decomposition (STL; Cleveland et al., 1990). STL is a very versatile and robust method to divide time series by detecting both gradual changes (trend) and cycles (season). More important, decomposing enables further analysis such as cross-correlation (CC) whose performance is affected by underlying temporal structures; hence it is strongly recommended that time series are de-trended beforehand.

STL consists in a sequence of Locally Weighted Regression Smoother (LOESS) procedures that split a time series into three components: trend, season and remainder (see Figure 12). For a detailed description of the algorithm see Cleveland et al. (1990). To facilitate understanding, season, trend and remainder will mean the following:

- **Season:** the component obtained that exclusively represents the positive and negative peaks of the detected seasonal cycles within the year.

- **Trend:** the component extracted from the time period that only takes into account the inter-annual evolution throughout the same, disregarding seasonal cycles.

- **Remainder:** the component that is left over from the two previous ones, and which therefore can be understood as anomalies or extreme events (both exceptionally high and low values) that are outside the average values of the trend and seasonal time series.

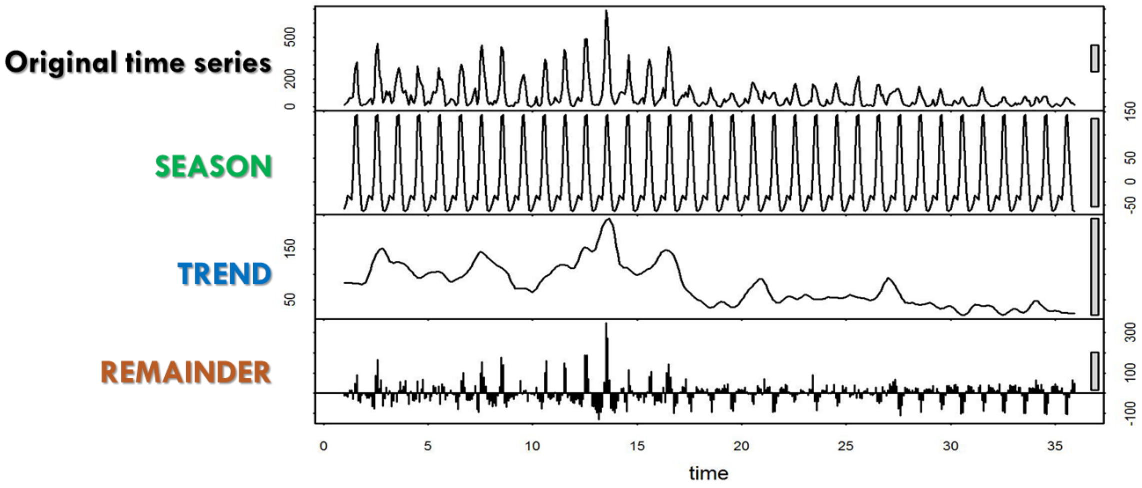

Figure 12. Example of fire frequency time series decomposition in the Mediterranean region of mainland Spain.

Autocorrelation Function (ACF)

This is one of the simplest methods to check that a time series fulfills the characteristic of being stationary. Specifically, the idea is to observe whether every signal differs by a high degree of 0 for each time lag. With this purpose in mind, the ACF signal graph is visualized. In particular, a stationary signal produces few significant delays exceeding the ACF confidence interval. In comparison, another time series with a trend would show that, in most of its time lags, the confidence interval of the ACF is exceeded.

Autoregressive Integrated and Moving Average (ARIMA)

To forecast the evolution of fire features, a set of auto-regressive, integrated and moving average (ARIMA) models were employed. They can be viewed as a "filter" that tries to separate the signal from the noise, and the signal is then extrapolated into the future to obtain forecasts. Their main advantage is that they adjust exclusively to the historical series of the input variable, which greatly reduces the complexity of the analysis, since it is not necessary to incorporate other explanatory variables. However, the main condition of ARIMA models is that time series are stationary, i.e. constant in mean and variance. As this condition is very difficult to find, all fire feature time series were previously transformed through the square root and then a de-transformation was applied to return to their original units. The future target period was set at 2016-2036, so that it would be the same length as the rest of periods. This exploration presupposed a continuous scenario in which it is assumed that the evolution of the factors associated with fire activity develop as observed in the whole historic period (1974-2015).

Monthly time series of fire features for the current period (1995-2015) were entered into the ARIMA. The reason was to include the seasonal component (intra-annual peaks and drops) because they would offer more information to the model so that the future projection would be as consistent and realistic as possible.

ARIMA offers several output data, the most important of which was the mean of the forecast, as well as the upper and lower limits of two confidence intervals (80% and 95%).

An automatic ARIMA was applied to obtain future fire regime features, returning the best model according to the minimum Akaike information criterion (AIC) value, so its algorithm automatically calculates the *p*, *i* and *q* parameters. As reported by Hyndman and Khandakar (2008), the seasonal ARIMA formula is established as follows:

$$\Phi(B^m)\emptyset(B)(1-B^m)^D(1-B)^d y_t = c + \Theta(B^m)\theta(B)\varepsilon_t \qquad (6)$$

where Φ(z) and Θ(z) are polynomials of orders P and Q respectively, each containing no roots inside the unit circle. If c≠0, there is an implied polynomial of order d + D in the forecast function. The main task in automatic ARIMA forecasting is selecting an appropriate model order, that is the values p, q, P, Q, D, d. When d and D are known, the rest of orders are chosen following an information criterion such as the AIC:

$$\text{AIC} = -2\log(L) + 2(p+q+P+Q+k) \qquad (7)$$

where k=1 if $c \neq 0$ and 0 otherwise, and L is the maximized likelihood of the model fitted to the differenced data $(1-B^m)^D(1-B)^d y_t$. The likelihood of the full model for y_t is not actually defined and so the value of the AIC for different levels of differencing are not comparable. In order to overcome this difficulty, for our case of seasonal data, we selected the seasonally differenced data D =1.

4.2.3. Classification and regression

Clustering

The fire regime delimitation was done by Ward's clustering method from the *NbClust* R package. This package provides a total of 30 indices for choosing the most adequate number of clusters and proposing the best clustering scheme from the different results obtained by varying all combinations of clusters (minimum and maximum desired), distance measurements and clustering methods. After several trial-and-error changing function parameters and according to the results obtained, the minimum and maximum number of clusters was established at 5 and 7, respectively. The distance selected was Canberra (Cd), and the method for the clustering outlined was Ward.D2. Cd was proposed by Lance and Williams (1967) and examines the sum of series of a fraction of differences between the coordinates of a pair of observations (Teknomo, 2015). In general, the Cd terms with zero numerator and denominator are omitted from the sum and treated as if the values were missing (Charrad et al., 2014). The formula of Cd is as follows:

$$Cd\,(x,y) = \sum_{j=1}^{d} \frac{|xj-yj|}{|xj|+|yj|} \qquad (8)$$

where *xj* is the first observation with coordinates of the features and *yj* is the second observation with its corresponding coordinates of the same features. Each term of fraction difference has value between 0 and 1, although in itself it is not really between zero and one. If one of coordinates is zero, the term becomes 1 regardless of the other value, thus the distance will not be affected. Consequently, Cd is very sensitive to a small change when both coordinates area near to zero. Therefore, Cd has the advantage of not being affected by the presence of zeros, which are abundant in some cells of the study area, more especially in fire features such as natural burned area and large burned area (above 100 has).

At each step the pair of clusters is chosen which leads to a minimum increase in the total within-cluster variance after merging. The Ward.D2 option implements Ward's clustering criterion in which the dissimilarities are squared before clustering updating.

K-Nearest Neighbor

In order to transfer current fire regime clusters for the remaining time periods (past and future), a KNN classification was performed. KNN is a nonparametric technique used in statistical estimation and pattern recognition (Ripley, 1996) widely used since the 1970's. The current period was taken as a benchmark, because it has more robust and reliable data. KNN trains for each grid in the test dataset (past and future fire features), finds the nearest *K* by a distance measure (Canberra distance), and the cluster class is decided by a majority vote of its neighbors. The *K* parameter means the maximum number of nearest neighbors considered in the algorithm (Venables and Ripley, 2002), being set in 5.

Generalized Additive Models (GAM)

In order to fulfil the first research objective for unravelling potential cause-and-effect relationships between fire features and climatic/human variables, several GAM regressions were calibrated for each Multidimensional Scatterplot (MDS) subset. Generalized Additive Models (GAM) are Generalized Linear Models (GLM) in which the usual linear relationships between the response and predictor variables are replaced by non-linear 'smooths' (Hastie and Tibshirani, 1986; Jones and Almond, 1992). The same as GLM, GAM can use probability distributions other than Gaussian, so we applied Negative Binomial to model the number of fires (N) and log linear distribution in burned area variables (B500, BL). NB is particularly suitable to deal with zero-inflated response variables, as is the case of N (Boadi et al., 2015). On the other hand, we applied a log linear family in burned area fire features (Hernandez et al., 2015). Model selection, is based on the reduction of Generalized cross validation (GCV, Craven and Wahba, 1978; Golub et al., 1979). GVC determines the optimal amount of smoothing and estimates the mean squared prediction error over all datasets where a single observation is omitted from the model fitting, and then predicted Deviance is explained (analogous to variance in a linear regression) and partial effects in the predictors were also calculated. All analyses for GAM modeling were conducted using the R package *mgcv*, version 1.8–9.

Random Forest

In order to assess the role of the drivers in fire regime change, we selected Random Forest (RF; Breiman, 2001) as the modeling algorithm, given its proven predictive accuracy (Bar Massada et al., 2011; Leuenberger et al., 2018a; Rodrigues and de la Riva, 2014a). RF is a tree-based ensemble algorithm that trains multiple decision trees by randomly bootstrapping the training sample, keeping 67% of the observations to train the decision tree and the remaining 33% (Out-of-bag, OOB) to evaluate the relative influence of the predictors and the model itself. The final stage assembles all trees into a final prediction as the average of all individual tree predictions (*Bagging*; Breiman, 2001).

For each fire regime transition type, we trained and validated 100 RF models, using a random sample of 70% for training and the remaining 30% for testing the performance of the model. At the training stage, we conducted a 10-fold calibration procedure to identify the optimal parameters (*mtry* and *ntrees*) of the model. At the same time, we also evaluated the influence of each driver by calculating the percentage increase in the Mean Square Error (normalized between 1 and 0), and its explanatory sense by means of partial dependence plots (J.H. Friedman, 2001). To estimate the predictive performance of each model carried out, we calculated the Area Under the Receiver Operating Characteristic Curve (AUC; Bradley, 1997). Additionally, the explanatory sense of the covariates (either positively or negatively related) was explored by visual inspection of partial dependence plots.

Geographically Weighted Regression Models (GWLR)

GWR is a statistical technique for exploratory spatial data analysis developed within the framework of Local Spatial Models or Statistics. Local models could be described as the spatial disaggregation of global statistics whose main characteristic is that it is calibrated from a set of spatially limited samples and, hence, yielding local regression parameter estimates (Fotheringham et al., 2002). Therefore, GWR techniques extend the traditional use of global regression models, enabling local regression parameters to be calculated. Mathematically, a conventional GWR is described by the following equation:

$$y_i = \sum_k \beta_k\,(u_i,v_i)\,x_{k,i} + \varepsilon_i \qquad (9)$$

where y_i, $x_{k,i}$, and ε_i are dependent variables, k_{th} is the independent variable, and the Gaussian error at location i;(u_i, v_i) is the x–y coordinate of the i_{th} location; and coefficients β (u_i, v_i) are varying conditionals on the location.

Such modeling 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 drawn 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, resulting in a set of local regression statistics. However, in this example, each point within the neighborhood is treated equally 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. In addition to the regression coefficients, a GWR model calculates several useful statistical parameters to analyze the spatial behavior of each explanatory variable, such as the value of the Student's t test, which is used to determine the level of significance. On the other hand, GLM approaches such as Geographically Weighted Logistic Regression (GWLR) and Geographically Weighted Poisson Regression (GWPR) have been incorporated to GWR to extend its functionality (Fotheringham et al., 2002; Nakaya and Fotheringham, 2009). The GWR approach has been already been explored in several papers such as Koutsias, Martínez-Fernández, & Allgöwer (2010), Martínez-Fernández et al. (2013) and Rodrigues et al. (2014). These two methodologies—GWLR and GWPR—are used in this study to complement the results from GLM. Several parameters have been included when calibrating GWR models. Kernel shape and type, bandwidth selection and optimization parameters, or the local or global nature of the predictors (see Nakaya and Fotheringham, (2009) for further details of both method and software). In this project, GWR model fitting was carried out using Fixed

Gaussian Kernel bandwidth, optimized according to the value of AICc, considering all the predictors as local covariates.

5 CHAPTER 5: SPATIAL-TEMPORAL DISTRIBUTION OF FIRE REGIME FEATURES

This chapter describes the results, discussion and main conclusions obtained from the analyses related to the identification of the major fire regime features and their temporal dynamics. We evaluate the relationships of fire features with climate gradients and human pressure, as well as the assessment of the contribution of small fires into the fire regime characterization. Multi-Group Principal Component analysis, GAM models, change point detection methods, Mann-Kendall and Sen' slope have been applied to fire features at regional and provincial level. The main goals are: describe and characterize the fire regime, identify its shifts and trends, determinate the extent to which fire regime is linked to climate-human factors and discover potential relations in the evolutions of fire features. Therefore, we seek to improve the understanding of the spatial-seasonal patterns of the key fire regime features.

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Understanding wildfires in mainland Spain. A comprehensive analysis of fire regime features in a climate-human context

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ABSTRACT

Understanding fire regime is a crucial step towards better knowledge of the wildfire phenomenon. However, the concept itself, in spite of its widespread use, still lacks a clear, widely accepted definition and there is no general agreement on which features define it best. In this paper we provide an in-depth characterization and description of fire regimes in three regions – Northwest, Hinterland and Mediterranean – comprising the whole of mainland Spain, to identify their key features. Data on number of fires, burned area, fire season and cause are retrieved from historical fire records for the period 1974–2010. Specifically, fire frequency, burned area, number of natural/human-caused fires, burned area from natural/human-caused fires, number of large fires (≥500 ha), and burned area from large fires were examined for each region and fire season. We used a multi-group Principal Components Analysis approach to determine the importance of each fire regime feature. Next, climate and socioeconomic variables were explored using Multidimensional Scatterplots and Generalized Additive Models to find the extent to which fire regimes are controlled by either environmental, human, or both factors. Results revealed differences among regions and seasons in terms of the characteristics of their respective fire regimes. However, several common features have been identified as key components of fire regimes, regardless of region or fire season: fire frequency, number of large fires, and burned area from natural fires. In addition, results confirm that fire regime in the Northwest area mainly depends on human activity, especially during winter, in contrast to the Mediterranean region.

1. Introduction

Wildfires are one of the major environmental disturbances worldwide, playing an important role in determining the structure and functioning of many ecosystems (Archibald, Lehmann, Gómez-Dans, & Bradstock, 2013; E. Chuvieco, 2009b; Ganteaume et al., 2013; Pausas & Fernández-Muñoz, 2012). Understanding the complex interactions of factors involved in wildfire activity still remains an unbeaten challenge, which usually involves dealing with complex interactions among numerous variables (Krawchuk, Moritz, Parisien, Van Dorn, & Hayhoe, 2009). In this regard, the analysis of fire regime is a crucial step towards a better comprehension of wildfires. This is especially relevant in the case of Spain, one of the most fire-affected areas within the European Mediterranean region in terms of annual cumulative burned forests (Darques, 2016).

Fire regime is usually defined as the average conditions of fire that are persistent and consistent within a particular area and over a given period (Chuvieco, 2009a, 2009b; Krebs, Pezzatti, Mazzoleni, Talbot, & Conedera, 2010). However, there is no agreement on how fire regime should be characterized, hence the term itself still lacks a clear and well-known definition (Krebs et al., 2010), although there is a list of potential variables describing fire regime commonly accepted (Pyne, Andrews, & Laven, 1996). Among the great variety of fire regime characteristics that are generally described, we found those such as frequency, seasonality, size, type, severity or intensity (Whitman et al., 2015). It is widely thought that fire regime components have been – and still are – highly variable across time and space (M. V. Moreno, Conedera, Chuvieco, & Pezzatti, 2014). Several studies have demonstrated that global fire regime has moved from being essentially controlled by climate factors to become more dependent on human activity (Chuvieco, 2009a, 2009b; Pechony & Shindell, 2010), thus evolving from natural to human fire regime. On a regional scale, and particularly in the case of Spain, climate still influences fire regimes. However, human impact has steadily gained importance over time (M. V. Moreno et al., 2014). In this respect, human influence on wildfire usually has a double-edge (Syphard et al., 2007). Fire suppression helps reduce the impact of fire activity (Chuvieco, 2009a, 2009b), but simultaneously, human pressure on wildlands is nowadays a major source of ignition

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(Wang & Anderson, 2010).

There are many factors involved when a fire regime characterization is approached (Murphy, Williamson, & Bowman, 2011). Despite considerable research being applied to distinguishing attributes belonging to different fire regimes or fire regions, it remains unclear which features should be included, and further research is still needed (Archibald et al., 2013). In this regard, an approach based on inter-regional and/or inter-seasonal comparison, such as the one we propose, might be particularly suitable. Due to the huge variability of fire activity, the best features to characterize fire regimes should be those that best differentiate regions and/or seasons. A first step toward capturing the main contrasts between fire metrics is to divide the whole period of study into two seasons. Even though fire seasonality has been little studied until now, it has proven useful in analysing the influence of human activities on fire regime (Le Page, Oom, Silva, Jönsson, & Pereira, 2010). Several authors have used different seasonal metrics as the median day of the fire season (Whitman et al., 2015), or the length of the fire season (Chuvieco, Giglio, & Justice, 2008) or to distinguish between two seasons inside a year (vegetative and non-vegetative) (M. V. Moreno et al., 2014).

In this paper we characterize and describe in detail fire regimes in three regions – Northwest (NW), Hinterland (HL) and Mediterranean (MED) – comprising the whole of mainland Spain, to identify their key features. We explore several fire regime features under the premise that there are different fire regimes across the Spanish territory, paying special attention to seasonality, cause and the impact of large fires (> 500 ha; San-Miguel-Ayanz, Moreno, & Camia, 2013). The assessment is developed from historical fire records for the period 1974–2010 from the General Statistics Forest Fires database (EGIF). Our first goal is to improve understanding of the spatial-seasonal patterns of fire regime features and analyse their influence on the fire regime itself. A second objective is to determine the extent to which fire regimes are linked to human and/or climate factors. To achieve these goals, we examined fire regimes from a quantitative and qualitative approach. The quantitative approach is based in a multi-group Principal Components Analysis which allows the most representative fire regime features to be identified and selected. In the latter, we combined the selected fire metrics with climate and human variables, and plotted their relationships using multidimensional scatterplots (MDS), then looked for patterns and relationships among these. MDS's outputs are complemented with Generalized Additive Models in order to better describe the potential relationships.

Fig. 1. Spatial distribution of the three regions and provincial division in mainland Spain.

2. Materials

2.1. Study area

The study area encompasses the whole of mainland Spain (excluding Balearic and Canary archipelagos and also the autonomous cities of Ceuta and Melilla) and covers a total surface area of 498,000 km^2. From a biogeographic point of view, mainland Spain is dominated by two different bioregions, Eurosiberian and Mediterranean. On the one hand, the Eurosiberian region covers the northern side of the country, including Galicia, the Cantabrian cornice and the Pyrenees and is characterized by an Oceanic climate, dominated by deciduous forest; while the Mediterranean region extends all over the remaining territory. This region is characterized by a Mediterranean climate, and is thus significantly drier and warmer than the Eurosiberian region. These conditions favour complex mosaics of plant communities of evergreen, deciduous and/or mixed forests, scrublands or natural grasslands.

Temperatures (Fig. A2, Appendix 1) vary from annual milder values in the NW provinces of the Eurosiberian region, dominated by an Oceanic climate; to warmer temperatures in the MED region, characterized by high annual thermal amplitude in the inner region and milder conditions towards the coast. The rainiest areas (Fig. A2, Appendix 1) are the Cantabrian cornice, and the highest mountain ranges as Pyrenees (Eurosiberian region) and the western Central System (inner Mediterranean region), with average values over 1000 mm per year and maximum during winter. On the other hand, the driest areas are located in the southeast and the Ebro Valley (inner Mediterranean region) and the province of Almeria (Mediterranean coast). Precipitation in the Mediterranean region is irregularly distributed both in time and space, with autumn-spring maximums. Human activity also changes its footprint across the territory. According to Corine Land Cover 2006, in the NW area approximately 68% of the region is covered by forests, shrubs or grassland. This land cover has been traditionally shaped by seasonal grazing at the end of the winter. In the HL region, there has been a progressive abandonment of agricultural activity (crops and pastures) which translates to around 54% of its territory being covered by wildland. Meanwhile, the Mediterranean region, the most populated area, is characterized by an extended wildland-urban interface, due to widespread urban development during the last few decades (M. V. Moreno et al., 2014).

Due to this variety of landscapes, climate and socioeconomic conditions, three different regions – NW, HL and MED – were used (Fig. 1), following the criteria from the Spanish Department of Defense Against Forest Fires (ADCIF). These regions outline homogeneous areas in terms of fire activity and seasonal averages, so that they are expected to have self-defining fire regimes (M. V. Moreno et al., 2014). The NW region includes the Autonomous Communities of Galicia, Asturias, Cantabria and the Basque Country, also the provinces of León and Zamora. This region is located within the Eurosiberian region, excluding the Pyrenees areas. Woodlands cover around 41% of this region which is characterized by long history of agricultural burning to maintain pastures and grasslands (M. V. Moreno et al., 2014). The HL region includes all of the Autonomous Communities without coastline, except for the provinces of León and Zamora (included in the NW region). This region, located in the Mediterranean biogeographical region, has the greatest woodland surface proportion of the whole country (approximately 61%) mostly due to abandonment of agricultural activities and lands (M. V. Moreno et al., 2014). Finally, the MED region (also in the Mediterranean biogeographical region) includes all the Autonomous Communities along the Mediterranean coast. It has the lower woodland proportion (roughly 22%) because of the high degree of urbanisation and tourism development.

2.2. Fire data

Fire data were retrieved from the General Wildfires Statistics (EGIF) database, one of the oldest 'complete' fire databases in Europe (M. V. Moreno, Malamud, & Chuvieco, 2011; Vélez, 2001). Specifically, fire records for 1974–2010 were selected and spatialized according to the 10 × 10 km UTM reference grid (referred to as fire grid) used by firefighting crews for approximate location of fire ignition points. Selected baseline information refers to sections 0, 1, 2, 4, 5 and 9 of the Spanish Forests Fire Reports (PIF) compiled in the EGIF database. Next, fire count data, total burned area size, ignition triggering date and fire cause were retrieved for each fire event, and later separated by season and region. Note that only information about fires ≥1 ha was used because small fires (≤1 ha) were not fully compiled until 1988. The temporal time span was established according to several factors. The starting year was set as 1974, since it was the first year to use the 10 × 10 km grid. Prior to that time, fire data were only recorded at province level, so grid information was not available. The ending year was selected on the basis of the availability of climate data from the MOTEDAS and MOPREDAS datasets (described below).

As stated before, regions were outlined following ADCIF specifications. In turn, two fire seasons were defined according to Moreno et al. (2014). Thus annual data were split into a spring-summer season (S), from April to September; and an autumn-winter season (W) from October to March. From all available fire data information, several fire regime features were then constructed for each region, fire season and grid cell: (i) fire frequency (F), calculated as the total number of fires; (ii) burned area size (B), as the total fire affected area; (iii) number of large fires (N500), as the total number of fires above 500 ha burned; (iv) burned area from large fires (B500), as the total affected area from fires above 500 ha; (v) number of natural fires, as the total number of fires with natural cause (NL); and (vi) burned area from natural fires, as the total burned area from fires with a natural cause (BL). Table 1 shows a statistical summary of the proposed features as well as some additional information regarding fire events with an anthropogenic source (NH/BH).

2.3. Climate data

Climate data were extracted from MOTEDAS (Monthly Temperature Dataset of Spain) and MOPREDAS (Monthly Precipitation Dataset of Spain) datasets. These datasets provide monthly climate information at a spatial resolution of 10 × 10 km, constructed from actual measurements from the Spanish Meteorological Network in the period 1951–2010 (Jose Carlos González-Hidalgo, Brunetti, & de Luis, 2011; José Carlos González-Hidalgo, Peña-Angulo, Brunetti, & Cortesi, 2015). MOTEDAS and MOPREDAS stand out as one of the most accurate databases in the context of climate data for mainland Spain. Their development was based on the reconstruction of meteorological data time series from each weather station in the region. In this paper, monthly data on annual average maximum temperature (T) and total precipitation (P) in the period 1974–2010 were extracted and adapted to the fire grid using a nearest neighbour procedure. Both maximum temperature and precipitation were later reclassified into 10 homogeneous (equal interval) categories (see Table A1 from Appendix 2), used to construct climate codes for the multidimensional scatterplots.

2.4. Land use, population and Human Pressure Index

Land use data were retrieved from Corine Land Cover 1990 (CLC), since it is centred on the temporal span. CLC information was used to outline the Wildland-Agricultural Interface (WAI) and the Wildland-Urban Interface (WUI), two variables strongly related to anthropogenic ignitions (Leone, Lovreglio, Martín, Martínez, & Vilar, 2009; Martínez, Chuvieco, & Martín, 2004; Rodrigues, de la Riva, & Fotheringham, 2014). The first represents the length of the boundary between agricultural and wildland areas, and the second, the length between populated and wildland areas. Both WAI and WUI were calculated at fire grid level (Marcos Rodrigues, Jiménez, & de la Riva, 2016). On the other hand, the Demographic Potential, which is an aggregate index for the ultimate future potential of the population, was retrieved from (Calvo & Pueyo, 2008) for 1991 at a spatial resolution of 5 × 5 km, later rescaled to the fire grid as the average value inside each cell. WAI, WUI and DP were normalized to a 0–1 interval and then aggregated to develop a Human Pressure Index (HPI, Fig. 2), representing the overall pressure of human activities likely to result in fire ignition.

3. Methods

As mentioned before, our methodology was based on quantitative and qualitative approaches. In the first case, we used multi-group Principal Component Analysis (MGPCA) to identity key fire regime features and then investigated their relation to climate and human activity, allowing us to describe and analyse fire regimes. This methodological approach is based on the one described in Whitman et al. (2015). However, instead of putting the focus on applying PCA to aggregate climate information and then exploring their relationships with fire data, we used MGPCA combined with a Varimax Rotation (VR) procedure to identify key fire regime features and then explore their association with raw climate and socioeconomic information. Finally, relationships among fire regime features, climate and human pressure were visually explored from multidimensional scatterplots representing the qualitative approach. Additionally, MDS were complemented by a regression analysis using Generalized Additive Models (GAM) to

Table 1
Statistical summary of fire regime features 1974–2010. S: spring-summer, W: autumn-winter. In brackets: first value corresponds to inter-region percentage; and second value to intra-region percentage. N: Number of fires, N500: Number of large fires (> 500 ha), NL: Number of fires by lightning, NH: Number of fires caused by humans, B: Total burned area, B500: Burned area of large fires (> 500 ha), BL: Burned area of fires by lightning, BH: Burned area of fires caused by humans. Burned area data expressed in km^2.

Region	Season	N	N500	N L	NH	B	B500	BL	BH
NW	S	98,039	513	1385	66,862	21,557	4778	472	14,212
		(40.8) (61.7)	(30.2) (81.9)	(26.8) (96.4)	(40.8) (59.1)	(34.6) (71.5)	(20) (82.2)	(12) (98.5)	(34.7) (68.5)
	W	60,614	113	52	4633	8586	1.035	7	6531
		(25.3) (38.2)	(6.6) (18)	(1) (3.6)	(28.3) (40.9)	(13.8) (28.5)	(4.3) (17.8)	(0.2) (1.5)	(15.9) (31.5)
HL	S	33,073	470	2492	19,289	12,958	6572	1747	7477
		(13.8) (73.2)	(27.6) (96.7)	(48.2) (99.1)	(11.8) (68)	(20.8) (89.6)	(27.6) (97.8)	(44.4) (99.9)	(18.2) (87)
	W	12,114	16	23	9073	1498	148	2	1112
		(5.05) (26.8)	(0.9) (3.3)	(0.4) (0.9)	(5.5) (32)	(2.4) (10.4)	(0.6) (2.2)	(0) (0.1)	(2.7) (12.95)
MED	S	28,289	513	1183	17,273	15,466	10,152	1686	10,158
		(11.8) (78.7)	(30.2) (87.2)	(22.9) (97.4)	(10.5) (77.4)	(24.8) (87.5)	(42.6) (89.7)	(42.9) (98.9)	(24.8) (87.1)
	W	7635	75	32	5032	221	1165	18	1508
		(3.2) (21.2)	(4.4) (12.8)	(0.6) (2.6)	(3.1) (22.6)	(3.5) (12.5)	(4.9) (10.3)	(0.5) (1.06)	(3.7) (12.9)
Total		**239.764**	**1700**	**5.167**	**163.859**	**62.275**	**23.85**	**3.932**	**40.998**

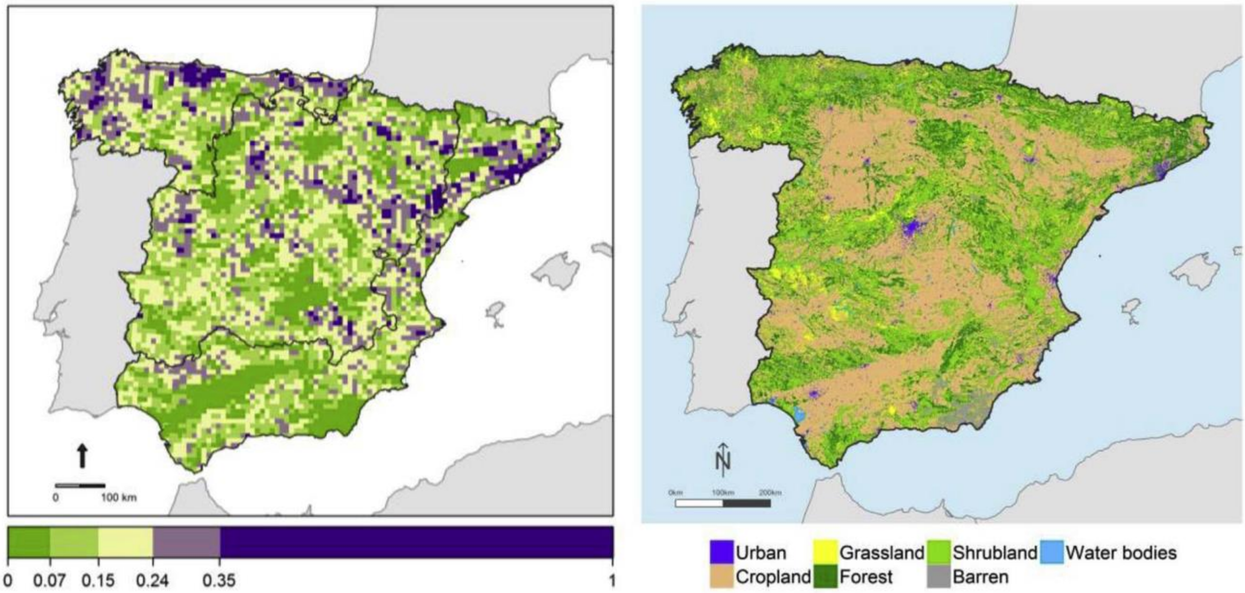

Fig. 2. Human Pressure Index (left) and generalized land cover from CLC 2006 (right).

provide deeper insights into the potential relationships among variables and features, as well as determine their statistical significance. All analyses, plots and maps were developed using the R statistical software (R Core Team, 2016).

3.1. Multi-group Principal Component Analysis and Varimax rotation

With the objective of identifying the most representative fire regime features from each region and season a PCA was carried out. PCA is a classic statistical technique that has been widely used in many research fields, and wildfire modelling is no exception. However, most of the examples of PCA applied to fire science are concerned with synthesising or reducing the amount of information for regression purposes (Francos, Pereira, Alcañiz, Mataix-Solera, & Úbeda, 2016; Fréjaville & Curt, 2015; Marcoux et al., 2015; Xu et al., 2006). It is even less common to apply PCA to fire regime feature analysis, even though some examples can be found in Drobyshev, Niklasson, and Linderholm (2012) and Quazi and Ticktin (2016). PCA estimates the common factors which explain the variance of the input parameters. Initially variables must be standardized so that each one has mean zero and unit variance, regardless of its scale. This ensures that all variables have the same weight in the analysis (Mardia, Kent, & Bibby, 1979).

Specifically, we used a multi-group PCA (MGPCA) procedure, which is an evolution of classic PCA (Krzanowski, 1984). MGPCA can be considered an evolution of common principal components analysis (CPCA) of multi-group datasets components analysis proposed by (Flury, 1984). CPCA is defined as a generalization of PCA to the case of multi-group setting. This consists in considering the variance-covariance matrices associated to the groups and seeking common orthogonal vectors of loadings associated with the components in the groups. However, the determination of the common vectors of loadings which is based on maximum likelihood estimation leads to a complex algorithm which is time consuming and whose convergence is not granted. MGPCA is simpler and more straightforward than CPCA (Eslami, Qannari, Kohler, & Bougeard, 2013b). MGPCA allows dealing with the variance-covariance between different groups (in our case regions and seasons). Hence, it is more suitable for group comparison (Eslami, Qannari, Kohler, & Bougeard, 2013a, 2013b) than ordinary PCA. We applied MGPCA splitting fire data into 6 different groups, one per region (NW, HL and MED) and season (summer and winter).

The Kaiser Criterion (Kaiser, 1960) was applied to MGPCA outputs, thus retaining only those PCs with eigenvalues greater than 1. Following this, a VR procedure was applied to determine the correlation between input variables (fire regime features) and PCs. VR consists of a PCA coordinates transformation which maximizes the sum of the variance, obtaining higher or near to zero coefficients, thus with fewer intermediate values. Consequently, the interpretation of PCA results becomes easier (Horst, 1965; Kaiser, 1958). For each PC we selected the fire regime features with a coefficient furthest from 0, identifying them as the most representative. We considered that these features contributed the most to the behaviour of fire activity across time (season) and space (region) and thus were key parameters in the definition of fire regimes.

3.2. Multidimensional scatterplots

Once the key fire regime features were selected, we examined the relationships between climate variables and fire features using multidimensional scatterplots (MDS). The construction process is as follows: (i) each grid cell in the study area was coded according to its respective combination of reclassified (from 1 to 10, see Table A1 in Appendix 2) temperature and precipitation (henceforth referred to as climate code); (ii) cells were then grouped on the basis of their respective climate code; (iii) fire regime features and HPI were aggregated as the sum and average value respectively; (iv) multidimensional scatterplots were then constructed. We created a two-dimensional climate space on the basis of climate codes for each region and season. On each plane, two additional variables were then plotted. N is always represented using proportional circles. Next, a fire regime feature was plotted on the N circles using different colour schemes. This led to multidimensional scatterplots, each one representing four variables (dimensions) in a single plot. Furthermore, in order to explore the relationship between human pressure, fire occurrence and climate, additional MDS were constructed representing HPI instead of fire feature. HPI was, therefore, only compared to climate and fire frequency as it mostly related to fire occurrence.

This kind of analysis has proved its potential in identifying relations amongst vegetation, climate and fire in Whitman et al. (2015). However, in our case we did not include a climate space. Instead, two climate gradients (temperature and precipitation) were used. Our goal was to determine the extent to which fire regimes are controlled by either environmental, human or both factors.

3.3. Generalized Additive Models

Generalized Additive Models (GAM) are Generalized Linear Models (GLM) in which the usual linear relationships between the response and predictor variables are replaced by non-linear 'smooths' (Hastie & Tibshirani, 1986; Jones & Almond, 1992). With the purpose of unravelling potential cause-and-effect relationships between fire features and climatic/human variables, we calibrated several GAM regressions for each MDS 'scenario'.

Same as GLM, GAM allows using probability distributions other than Gaussian. In this sense, we employed Negative Binomial to model number of fires (N) and log linear distribution in burned area variables (B500, BL). NB is found particularly suitable to deal with zero-inflated response variables as is the case of N (Boadi, Harvey, & Gyeke-dako, 2015). On the other hand, we have applied log linear family in burned area fire features (Hernandez, Keribin, Drobinski, & Turquety, 2015). Model selection, is based on the reduction of Generalized cross validation (GCV, Craven & Wahba, 1978; Golub, Heath, & Wahba, 1979). GVC determines the optimal amount of smoothing and estimates the mean squared prediction error over all datasets where a single observation is omitted from the model fitting and then predicted Deviance explained (analogous to variance in a linear regression) and partial effects in the predictors were also calculated. All analyses were conducted using the R package mgcv, version 1.8–9.

4. Results

4.1. Fire regime key features

MGPCA enables the comparison of fire regions as well as determining the most relevant fire regime features. Regardless of the region or season of analysis, 3 PCs were always selected according to the Kaiser Criterion. Therefore, PCA results are only presented and analysed for the 3 first PCs (PC1, PC2 and PC3). Hence, VR was only calculated for those PCs.

According to MGPCA eigenvectors (Table 2), most of the total variance (61%) in fire activity in the NW region during summer is associated with large fires, both in terms of number and the affected area (N500, B500 = 0.50). N appears on a secondary plane located in PC2 and associated with human fires (0.69). This behaviour is reversed during winter, when N and NH are promoted to PC1 and N500-B500 moved to PC2. In the HL region large fires seem to be playing an important role in both summer and winter, being in both cases located in PC1, although winter shows a strong link between B500 and BH. Finally, in the MED region, PC1 in summer correlates more with NH and N (0.51 and 0.5 respectively). During winter, B500 displaces N and NH towards PC2 being associated to BH (0.46). Whatever the region or season, the impact of natural fires is always in PC3. In this regard, there is usually a higher correlation between burned area rather than fire counts.

Features selected on the basis of the MGPCA-VR procedure are mostly the same across regions and seasons –N, B500 and BL– although there are differences in terms of the PC which each feature is associated with. As stated before, we consider these features to contribute the most to the behaviour of fire activity across time (season) and space (region) and thus to be key parameters in the definition of fire regimes.

4.2. Climate-human-fire relationships

Figs. 3–5 display MDS for N500, BL and N, respectively, whereas Table 3 and appendix S3 summarize the main outputs from GAM. According to Figs. 3–5 we can identify two different climatic patterns and a transition in fire activity from NW region to HL and MED. Most of the fires ignite during summer, regardless of the region. Nonetheless, the proportion of winter wildfires is larger in NW than in any other region, with nearly 40% occurring during winter (Table 1). Summer number fires (Figs. 3–5) in NW appear to be associated with mid-range temperatures (T3-7) and mid-to-low precipitation (P6-2). NW winter fires are mainly related to relatively high temperatures (T7-8) and moderate rainfall (P5). GAM reports significant relationships for both climate variables, adding human pressure as significant predictor in all seasons. Partial plots revealed a positive association during summer of N with temperature and human pressure (i.e. the higher the temperature or human pressure the higher the number of fire events). In winter temperature shifts towards negative relationship whereas human pressure remains positive. Through HL to MED, N becomes closer to higher T and lower P in both seasons as climate conditions change from Oceanic to inner Mediterranean, finally reaching the Mediterranean climate domain on the coast. However, HL summer fires take place mainly in areas with very high temperatures (T9-10), whereas in MED, the temperature interval widens to 6–10. On the contrary, MED fires occur in areas with lower precipitation than fires in HL. This difference is also evidenced in GAM models which report non-significant relationship with T and significant in P in the Mediterranean region, and the opposite in HL (see Figs. A4 and A5). In turn, winter fires in HL are less selective, occurring under different conditions while MED shows fewer seasonal differences, and fires ignite under roughly the same conditions, i.e. high T (6–10) and low P (1–4) during winter or summer.

Table 2
Correlation values according to Varimax Rotation, variance explained (% var) and specific variance of groups (Var) extracted from MGPCA. Selected features (correlation > 0.5) highlighted in light grey.

	NW S			HL S			MED S			NW W			HL W			MED W		
	PC1	PC2	PC3	PC1	PC2	PC3	PC1	PC2	PC3	PC1	PC2	PC3	PC1	PC2	PC3	PC1	PC2	PC3
% var	**61.2**	**15.1**	**13.1**	**55.1**	**17.6**	**11.4**	**48.4**	**20.4**	**11.2**	**49.8**	**17.8**	**17.6**	**46.4**	**18.9**	**17.6**	**46.7**	**18.5**	**15.8**
Var	**4.89**	**1.20**	**1.05**	**4.41**	**1.41**	**0.91**	**3.87**	**1.63**	**0.90**	**3.98**	**1.42**	**1.41**	**3.71**	**1.52**	**1.41**	**3.73**	**1.48**	**1.26**
N		-0.66			-0.65		0.50	-0.14		0.61	-0.15			-0.70			-0.61	
B	0.47			0.46		0.14	0.44	0.18		0.40	0.28		0.48	-0.14	0.11	0.46	-0.18	
N500	0.50	0.11		0.50				0.78			0.60		0.42			0.44		
B500	0.50			0.53	0.15	0.16		0.66			0.64		0.52	0.19		0.63	0.22	
NL		-0.16	0.70		-0.21	0.67			0.88		-0.10	0.67	-0.10	-0.10	0.69			0.58
BL		0.14	0.75	0.10	0.16	0.72			0.38			0.69		0.13	0.67		0.18	0.88
NH		-0.69			-0.65		0.51	-0.15		0.61	-0.15			-0.69			-0.59	
BH	0.46	-0.11		0.48	-0.12	-0.20	0.42	0.13		0.40	0.27		0.50	-0.16	-0.16	0.45	-0.11	

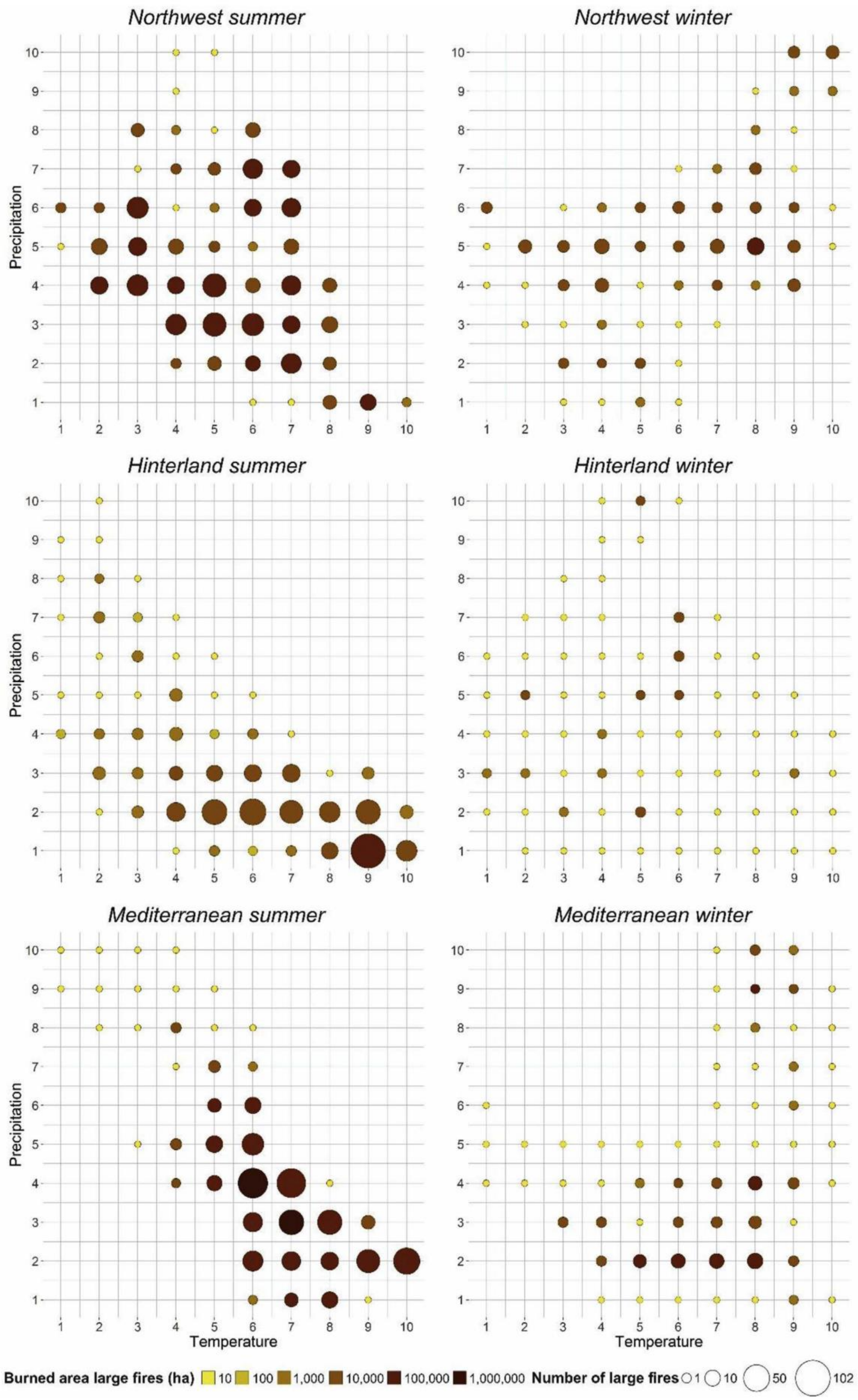

Fig. 3. Multidimensional scatterplots for burned area from large fires. Note values are given on the logarithmic scale.

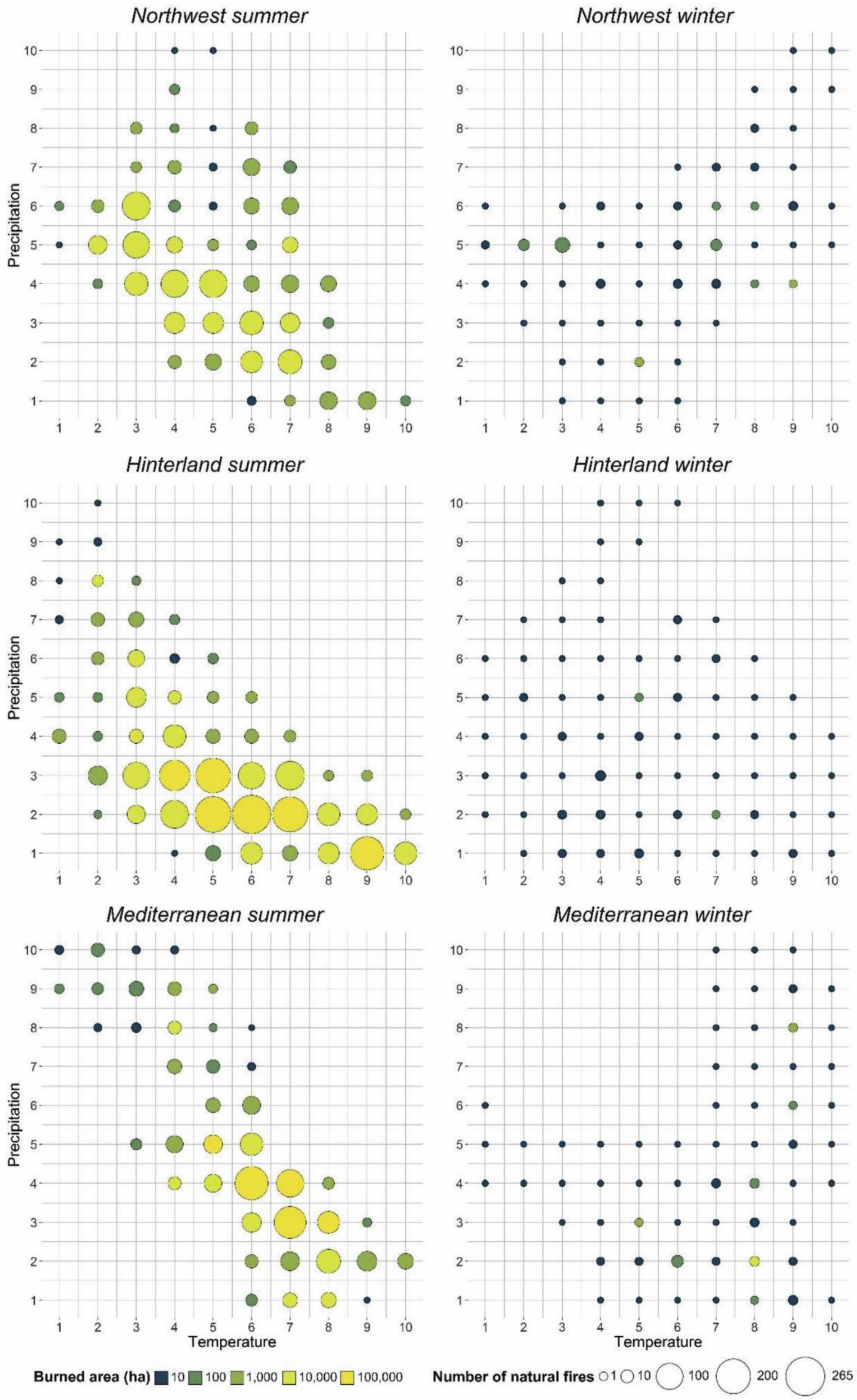

Fig. 4. Multidimensional scatterplots for burned area from natural fires. Note values are given on the logarithmic scale.

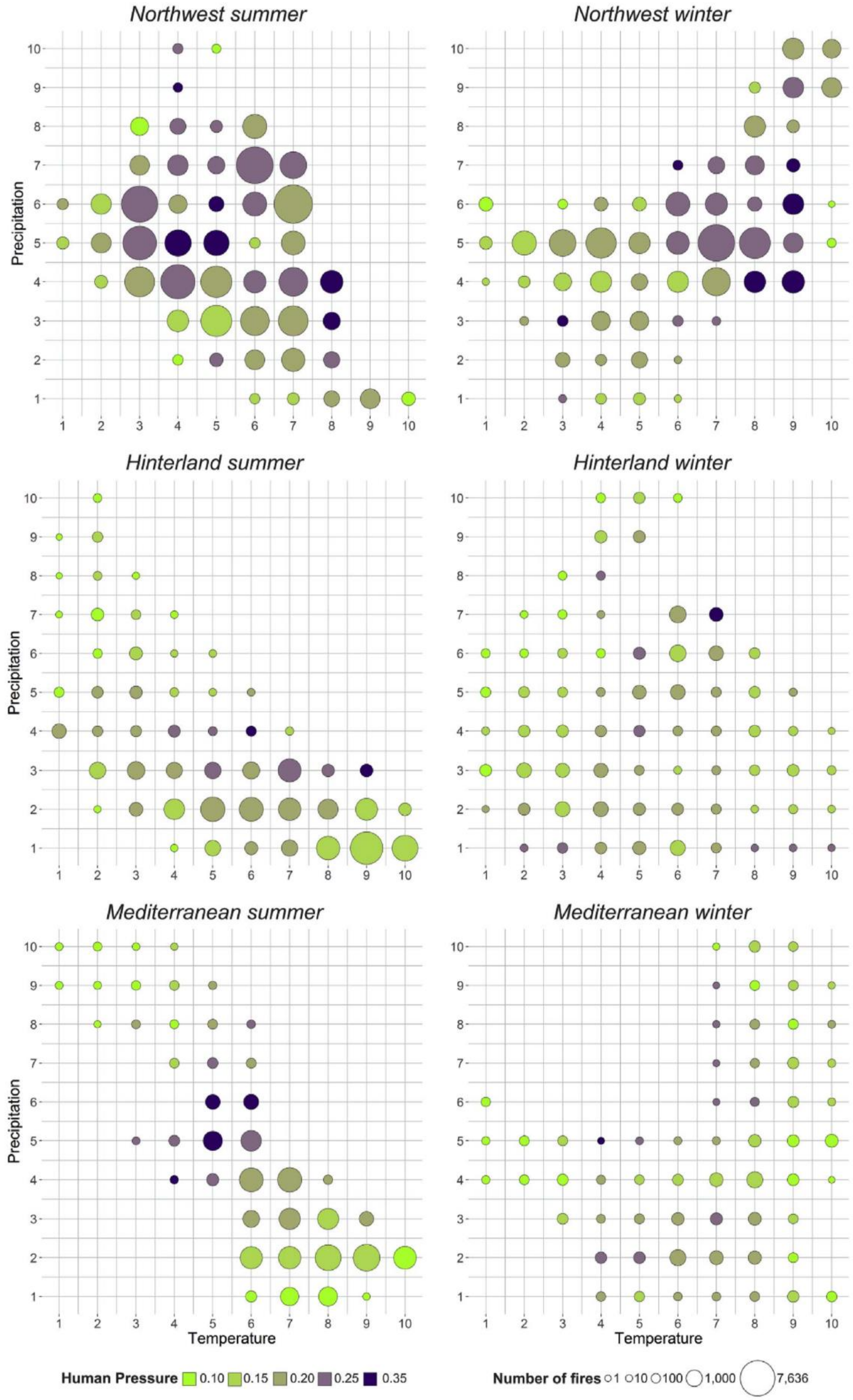

Fig. 5. Multidimensional scatterplots for HPI. Note values are given on the logarithmic scale.

Table 3
Deviance explained (DE) and p-values of the GAM outputs for each fire feature with reclassified data of temperature (T), precipitation (P) and human pressure (H) in the three regions and both seasons (S: spring-summer, W: autumn-winter). Negative binomial distribution was applied for number of fires (N) and log linear family for burned area ones (BL and B500). Bold values are significant (< 0.05).

	DE	NW S			*DE*	HL S			*DE*	MED S		
		T	P	H		T	P	H		T	P	H
N	0.41	**0.000**	**0.000**	**0.000**	0.14	**0.000**	**0.000**	**0.000**	0.2	0.074	**0.000**	**0.000**
BL	0.18	0.644	**0.000**	–	0.10	**0.035**	0.104	–	0.2	0.492	**0.039**	–
B500	0.17	**0.012**	**0.000**	–	0.12	**0.000**	**0.000**	–	0.13	0.245	**0.000**	–
	DE	NW W			*DE*	HL W			*DE*	MED W		
		T	P	H		T	P	H		T	P	H
N	0.42	**0.000**	**0.000**	**0.000**	0.32	**0.000**	**0.000**	**0.000**	0.21	**0.000**	**0.000**	**0.000**
BL	0.2	0.062	**0.000**	–	0.2	**0.000**	**0.000**	–	0.31	**0.000**	**0.000**	–
B500	0.15	**0.013**	0.093	–	0.3	0.2	**0.000**	–	0.25	**0.034**	**0.000**	–

As with N, B500 shows different behaviour across regions and seasons with NW as the most fire-prone region (Fig. 3). The pattern is, to some extent, similar to that of N, as areas with a large occurrence of fire are more likely to retain most burned area, regardless of burned size. During summer, NW appears to be associated with relatively low P (3–4) and moderate intervals of T (P3-7), although relationships are found to be significant. However, during winter, most of the burned area from large fires is located in areas with high T (8) and moderate P (5), with P losing significance in GAM models. Note that B500 in winter is more strongly linked to high T than N (see Fig. A3). In HL and MED, B500 behaves mainly in the same way as N, with the exception of summer wildfires in MED, where most of the area from large fires converges between P3-4 and T6-7, being more linked to P (significant $p < 0.05$) than T (non-significant).

Fig. 4 summarises the results from BL analysis. Again, the climatic pattern shows differences between NW and HL-MED. On the other hand, by putting BL and B500 together, we can establish some interesting associations. To a certain extent, there is a link between B500 and BL. In NW summer, the area from natural fires has its maximum values in several spots in P3-6 (significant $p < 0.05$) and T3-7 (non-significant). This pattern matches a part of B500 quite closely, suggesting that large summer fires under these conditions are mostly caused by natural ignitions. This association strengthens in HL and MED regions – again only during summer. GAM detects several significant relationships among T and P although no clear explanatory sense is observed in partial plots (Figs. A3–A5) other than P in NW winter.

Attending to the percent of deviance explained we found large differences among regions and seasons, in terms of the overall explained variance, and thus reliability. DE ranges from 0.42 to 0.41 in number of fires in NW regardless of the season to 0.13 in B500 in MED summer. Overall, winter DE values are higher than summer, especially in HL and MED. Lowest proportion of variance explained is usually obtained for natural fires.

Finally, an exploration of the relationship between N and HPI provides some remarkable insights. The link between N and human activity is noticeable. For instance, MGPCA (Table 2) reveals an association between N and NH in any given region or season; likewise GAM outputs report significant and positive relationships among N and HPI (Table 3 and Figs. A3–A5). According to the results in Fig. 5 and Fig A3, HPI mainly relates similarly to N in the NW region both during summer and winter. However, the relationship is slightly stronger in winter, although this association is less evident in HL and MED, especially during winter (decreasing contribution, see Figs. A4 and A5), this fact is also supported by a lower deviance explained. In NW, summer fires ignited at low T (3–4) and moderate P (4–6) present high HPI average values. During winter, almost every combination of P and T, taken from over 100 fires, have HPI average values around or higher than 0.2. Both in HL and MED summer, high HPI values are mostly located in T5-7 and P2-6.

5. Discussion

This paper characterizes and describes in detail fire regimes in mainland Spain, to identify their key features under the premise that different fire regimes exist across Spanish territory. We proposed a combination of statistical (MGPCA, VR and GAM) and visual techniques (MDS) as an approach to understanding climate-human-fire relationships, enabling the easy identification of contrasts in fire regime among the different regions analysed. This is particularly noticeable in the Northwest region, where fire behaviour is dissimilar to the rest of the study area in terms of both fire behaviour and ignition cause. In other words, fires are more frequent in Northwest, less related to climate conditions and more dependent on human pressure, whereas Hinterland-Mediterranean are more influenced by climate with greater seasonal differences.

Multi-group PCA combined with VR has led to identifying large fires (B500 and N500), overall fire frequency (N) and burned area of lightning fires (BL) as the features strongly relating to fire activity, and thus considered as key fire regime features. In addition, MGPCA also enables the importance of each fire feature to be explored. For instance, depending on the PC that a given feature is related to, we can determine its importance. In this regard, we have identified two different seasonal behaviours. Summer fire activity is more closely related to fire frequency (N located in PC1) and the impact of large fires appears on a secondary plane (B500 and N500 correlate more to PC2), whereas winter shows the opposite. In fact, in the case of the Northwest region the seasonal reversion of its components suggests that summer fire activity is mostly related to the impact of large fires, whereas winter fire behaviour is better explained by fire frequency from anthropogenic wildfires. In turn, the impact of natural fires, despite being systematically selected among the available features, always appears in PC3 both in terms of fire counts (NL) and affected area (BL). Varimax rotation results show that burned area coefficients are generally higher. Thus, natural fires appear to be better characterized in terms of affected area rather than number of fire events. Finally, MGPCA allows us to investigate the relationships among fire features. In this respect, the most relevant finding is that fire frequency (N) is always associated with anthropogenic fires (NH). On the one hand, this supports the hypothesis that Spanish fire regime is human-dominated (Rodrigues et al., 2014; San-Miguel-Ayanz et al., 2012).

The visual inspection of the MDS and the statistical interpretation of GAM models are particularly useful in terms of pyrogeography, i.e. the spatial distribution of fire regime features and their relationship with climate and socioeconomic factors (Fréjaville & Curt, 2015). These

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Table 4
Summarize of the main fire features characterizing and median values of climatic variables (reclassified, see Table A1 of Appendix 2 for original values) and human pressure (H) for each region and season. More representative fire features are highlighted with a tic symbol (✓) according to MGPCA results. Colors represent the sign of estimate effects (Red: Increase, Orange: Stable or very variable, Green: Decrease) of the relationship between fire feature and climatic/human variables (see Figs. A3–A5 for details). Asterisks represent significant relationships between fire features and climate/human variables.

	NW S				HL S				MED S				NW W				HL W				MED W			
		T	P	H		T	P	H		T	P	H		T	P	H		T	P	H		T	P	H
		5	4	0.2		6	2	0.1		7	2	0.1		6	5	0.2		5	2	0.1		8	4	0.1
N	✓	*	*	*	✓	*	*	*	✓		*	*	✓	*	*	*	✓	*	*	*	✓	*	*	*
BL	✓		*		✓	*					*		✓		*		✓	*	*		✓	*	*	
B500	✓	*	*		✓	*	*		✓		*		✓	*			✓		*		✓	*	*	

procedures were applied to the selected key fire features. The analysis reveals that the NW fire regime, which is mostly dependent on human activities, is in contrast to Hinterland and Mediterranean. It is well known that in Northwest, fire is traditionally involved in several activities such as pasture burning and grazing (M. V. Moreno et al., 2014) close to forest areas. Conflicts between landowners or individuals and the forest administrations leading to arson are another particular characteristic of this area, where deliberate fires have increased since the early 90s (Leone et al., 2009). In any case, it is clear that human activity is responsible for, or at least has helped in shaping fire regime in the Northwest region. Moreover, winter fires are most frequent here than in any other region, not only in terms of number of fires, but proportion of overall fires. This fact makes the region particularly difficult in terms of wildfire modelling, since most of the variables used are usually concerned with summer fire activity (M. Rodrigues et al., 2014). On the other hand, wildfires are especially numerous during early spring coinciding with south winds (M. V. Moreno et al., 2014). In this case, there is an evident association between the hotter and drier conditions in this season, linked to this particular weather and, once again, to human factors – intentional fires peak (M. V. Moreno et al., 2014) – (Fig. A6 in Appendix 3 and Fig. 5).

Hinterland and Mediterranean regions share more similarities than differences. These regions show a stronger dependency on climate factors than Northwest. In fact, human pressure is generally associated with climate conditions unlikely to ignite fires, thus complementing the influence of climate. During summer, HL shows significant and positive relationships among N, B500 and temperature and negative with precipitation while MED displays significant relationships with precipitation alone. As expected, fire features adapt to the climate gradient. For instance, in these regions, natural fires play a more decisive role since they are more linked to burned area from large fires, so they have a greater impact in terms of affected area. Or what is the same, a high proportion of large fires in HL and MED regions have a natural source. Natural fires usually hinder suppression tasks, since accessibility to the burning area may be significantly difficult. Thus natural fire has a higher chance of propagating than human-caused fires since climate and fuel conditions are usually favourable (Chuvieco, 2009a, 2009b). Therefore, we can safely assume that natural fires explain, or at least have some involvement with, a part of the burned area from large fires. HL, which can be considered as a transition area between pure Eurosiberian conditions to Mediterranean ones, is still influenced by human activities, although human factors are somewhat complementary to climate conditions. Multi-group PCA supports this to some extent. PC1 meets large fire activity with burned area from human-caused fires, suggesting that winter wildfires may have a human origin. The reasons explaining this fact may be found in agricultural practices or in negligence and accidents from recreational use of forest areas (Leone et al., 2003). With regard to the MED region, the situation is slightly different compared to HL. Fire frequency and total affected are more influenced by climate, specifically by precipitation or better the lack of it. The more important role of precipitation and the lesser human influence is manifested in the huge area of large fires, greater than any other region (Table 1), favoured by dry fuels, something that several authors have previously pointed out (Pausas & Fernández-Muñoz, 2012; Pausas, 2004; Vázquez, Climent, Casais, & Quintana, 2015).

In summary (Table 4), we can state that fire regime is strongly influenced by human activities in each region and season. Wildfire frequency is always significantly related to temperature, precipitation and human pressure, except in the case on MED during summer which is only tied to P and HPI. Large fires exhibit a strong relationship with precipitation during summer, being also linked to high temperature in HL. Natural fires are somewhat tied to large fires although better explained by precipitation. Finally, from a seasonal standpoint, winter is perhaps the most complex season of the year, due to climate conditions losing part of their influence and human activities taking over, especially evident in the case of the NW and HL regions.

Nevertheless, our research has several limitations that must be pointed out. Firstly, our analysis is focused on a single study period (1974–2010), and even though it includes the seasonal scale, does not include temporal evolution of fire features, and fire activity has most likely changed over the temporal span (see Moreno et al., 2014). On the other hand, the scope is focused on several features extracted and constructed on the basis of the available fire information. However, other fire metrics beyond fire reports (e.g. fire severity or intensity) may be included in further analysis.

6. Conclusions and further research

In this paper, we have described and characterized the major characteristics of the fire regimes in Spanish mainland through quantitative and visual analyses of relationships between fire components, climate and human pressure, using fire data from 1974 to 2010. We were able to determine the most important fire regime features and analyse fire regime on that basis. Our results suggest that not all the regions examined have the same fire regime, although they share some characteristics, as in the case of HL and MED during summer.

The combination of multi-group PCA techniques with visual analysis of multidimensional scatterplots and GAM regression has proved to be a powerful toolset that enables characterization and investigation of fire regimes. On the one hand, MGPCA has revealed that the main features of Spanish fire regimes are total frequency of fires, burned area from fires over 500 ha big and burned area of natural fires. In addition, the analysis of these fire regime features in the context of climate and human factors enabled the main drivers behind fire regime characteristics over regions and seasons to be established. In this sense, the NW region represents a paradigmatic example of the impact from human factors, especially during winter, whereas Hinterland and Mediterranean regions are mostly dependent on climate conditions.

Overall, the NW region is characterized by fire frequency and large fire activity during summer, whereas during winter, anthropogenic fires play a more important role. HL reproduces the same behaviour, human fires during winter and large fires during summer. Finally, MED is characterized by burned area metrics, whereas fire frequency is located in first place during summer but remains in second place, during winter. In any case, fire activity shows contrasting characteristics among regions and seasons. Therefore, fire modelling should take this seasonality into account in order to produce more reliable results.

The identification of key features opens new research lines that shall be further investigated. For instance, the spatial and temporal variability of fire regimes must be explored in depth. This means that, rather than consider homogeneous regions (e.g. NW, HL and MED), we must outline them on the basis of fire features. On the other hand, deeper insights into the temporal evolution of fire regimes have to be provided, since fire activity has most likely changed over the years, the same as climate and human factors on which they are dependent.

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Appendix A. Supplementary data

Supplementary data related to this article can be found at http://dx.doi.org/10.1016/j.apgeog.2017.10.007.

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Exploring spatial–temporal dynamics of fire regime features in mainland Spain

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Abstract. This paper explores spatial–temporal dynamics in fire regime features, such as fire frequency, burnt area, large fires and natural- and human-caused fires, as an essential part of fire regime characterization. Changes in fire features are analysed at different spatial – regional and provincial/NUTS3 – levels, together with summer and winter temporal scales, using historical fire data from Spain for the period 1974–2013. Temporal shifts in fire features are investigated by means of change point detection procedures – Pettitt test, AMOC (at most one change), PELT (pruned exact linear time) and BinSeg (binary segmentation) – at a regional level to identify changes in the time series of the features. A trend analysis was conducted using the Mann–Kendall and Sen's slope tests at both the regional and NUTS3 level. Finally, we applied a principal component analysis (PCA) and varimax rotation to trend outputs – mainly Sen's slope values – to summarize overall temporal behaviour and to explore potential links in the evolution of fire features.

Our results suggest that most fire features show remarkable shifts between the late 1980s and the first half of the 1990s. Mann–Kendall outputs revealed negative trends in the Mediterranean region. Results from Sen's slope suggest high spatial and intra-annual variability across the study area. Fire activity related to human sources seems to be experiencing an overall decrease in the northwestern provinces, particularly pronounced during summer. Similarly, the Hinterland and the Mediterranean coast are gradually becoming less fire affected. Finally, PCA enabled trends to be synthesized into four main components: winter fire frequency (PC1), summer burnt area (PC2), large fires (PC3) and natural fires (PC4).

1 Introduction

Wildfire is a disturbance affecting many ecosystems on a global level. Fire itself is a very dynamic landscape process, which depends on different factors, such as weather, vegetation type and structure, fuel moisture, land use and human activity (Falk et al., 2011). Understanding wildfire phenomenon is still a challenging task, especially when facing climate and/or socioeconomic changes (Pausas and Keeley, 2009) as is the case of Spain (Pausas, 2004; Pausas and Fernández-Muñoz, 2012; Turco et al., 2014) and other EUMed regions (Moriondo et al., 2006; Salis et al., 2014; Venäläinen et al., 2014). In this context, fire regime characterization may contribute to improving our knowledge on how wildfires generally behave. For example, understanding spatial and temporal patterns of wildfire features may lead to more effective management strategies or prevention policies.

Improved understanding of fire regimes may be achieved by providing deeper insights into the spatial patterns of fire regime features over a certain period of time (i.e. homogenous areas with similar fire regime characteristics). From a temporal perspective, previous studies reported the existence of temporal changes or trends in the evolution of several fire regime features (Flannigan et al., 2009; Rodrigues et al., 2013; Turco et al., 2016). However, despite there being evidence of temporal variability in fire regime features, it is not usually considered when defining, characterizing or outlining fire regimes. The concept of fire regime is commonly defined as the average conditions of fire that remains recurrent and consistent within a particular area and occurring over a certain period of time (Krebs et al., 2010). According to this definition, it seems clear that both space and time are taken to be stationary, but fire regime components are

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in fact highly variable across time and space (Morgan et al., 2001). Recently, several works studying fire regimes were conducted in Spain, among which those by Moreno and Chuvieco (2012) and Moreno and Chuvieco (2016) are notable as the latest attempts to deal with fire regime characterization. However, in these works, the behaviour of fire regime features is still assumed to be homogeneous or stationary over time. To our understanding, the concept or definition of fire regime has to include changes in fire features over the study period. This is ultimately the goal of our proposal: to characterize the temporal evolution of fire regime features so that they can be employed to refine and improve the spatial outline of fire regimes, for example, by using trend outputs as an additional input of the cluster or zoning algorithm.

Analyses of spatial–temporal trends of fire regime features are common in the literature. The most widespread approach addresses changes in fire frequency and burned area (Kasischke and Turetsky, 2006; Pausas and Fernández-Muñoz, 2012; Rodrigues et al., 2013; Zavala et al., 2011). In the Mediterranean region, the main findings indicate a general decrease during the period 1985–2011 (Turco et al., 2016) in the annual number of wildfires and burned area, although a certain spatial variability is observed in the trends. For instance, over the last few decades, the burned area in Spain has decreased. Conversely, the yearly number of fires has increased, except on the Mediterranean coast (Turco et al., 2016). However, most studies focus mainly on analysing "generic" fire (number of fires and burned area). This is particularly true for Spain, which lacks a detailed analysis of fire trends based on a spatial–temporal approach. We believe that a proper characterization of fire regime must take into account additional features, such as fire size, cause or seasonality. Even though some studies dealing with the temporal dimension of wildfires do exist (Serra et al., 2013), most of them present some limitations, such as a short time series (less than 20 years of data). Meanwhile, analyses using a longer time series do not include many fire regime features and stay with the overall number of fires and burned area (Pausas, 2004; Pausas and Fernández-Muñoz 2012; Moreno et al., 2014). Specifically, we stress the importance of assessing the evolution of large fires (fires with more than 500 ha burned; San-Miguel-Ayanz et al., 2013) and the potential differences relating the ignition source of a wildfire, either natural or human caused.

Therefore, the analysis of the temporal dimension of fire regime features must be extended to these other features in order to provide a more detailed picture of the evolution of fire activity with the ultimate goal of characterizing fire regimes. Similarly, advances must be made in applying trend detection procedures. Determining whether a certain feature changes significantly is useful but not sufficient. Further insights into trend magnitude must be provided so that we can compare trends among several regions and explore possible relationships among temporal changes in fire features.

The aim of this study is to analyse spatial–temporal trends of several fire features during the period 1974–2013 and explore potential relationships among those detected. In addition, this work would also allow progress and further developments in the fire regime zoning. The analysis is conducted at several spatial, such as regional and NUTS3/provincial level, and autumn–winter and spring–summer temporal scales in mainland Spain. Data on fire regime features were retrieved from historical fire records stored in the EGIF (General Wildfires Statistics) database. Firstly, seasonal shifts in the evolution of fire feature were examined using change point detection techniques in three different regions comprising the whole of mainland Spain. We used several checkpoint techniques to determine if and when significant changes in the temporal evolution of each fire regime feature takes place. Trend detection procedures were then applied at the two different spatial levels to address the spatial–temporal variability of each fire feature. The purpose was to determine whether fire features vary over time and, if so, its sign – upward or downward – and strength. Finally, complementary analyses were applied to uncover potential links in the evolution of fire features.

2 Study area

The study area encompasses the whole of mainland Spain (thus excluding the Balearic and Canary archipelagos and the autonomous cities of Ceuta and Melilla). Spain is very biophysically diverse, presenting a wide variety of climatic, topographical and vegetation communities. This diversity also appears when discussing socioeconomic conditions in terms of settlement systems and population structure, production sector, changes in land use and land cover, or structure of the territory.

From a climatic perspective, mainland Spain is characterized by contrasting climatic conditions. According to the Spanish Climate Atlas (AEMET, 2011) and based on the Köppen–Geiger climate classification system (last version from 1936) we found cold (D), temperate (C) and dry (B) climates. Csa (temperate with dry or hot summer) is the type of climate which covers most of the Iberian Peninsula, occupying approximately 40 % of its surface. It covers the majority of the southern central plateau region and the Mediterranean coastal regions, with the exception of the arid zones in the southeast, where we found BWh (hot desert) conditions. Cold climates are located in the highest mountain ranges in both the Pyrenees and Iberian mountain ranges (Dfb-c) and also in small areas of the mountainous regions at higher altitudes in the Cantabria Mountains, the Iberian mountain ranges, Central Ranges and the Sierra Nevada (Dsb-f). Finally, Cfa (temperate with a dry season and hot summer) is mainly seen in the northeast area, within an area of medium altitude which surrounds the Pyrenees and the Iberian mountains.

From a biogeographical point of view, mainland Spain is divided in two biogeographical regions: Eurosiberian, located in the northwestern area, and the Mediterranean, covering the remaining area. The Eurosiberian area is mostly covered by various types of vegetation from deciduous oak and ash to evergreen oak woodlands (*Quercus robur*, *Fraxinus excelsior* or *Fagus sylvatica*), but this region also has a quite important component of forest plantations such as *Pinus radiata* and *Eucalyptus globulus*. In turn, the Mediterranean region presents complex mosaics of agricultural systems and plant communities. Sclerophyllous and evergreen vegetation, such as *Quercus ilex, Quercus suber* and thermophilous scrublands (maquis and garrigue formations), dominate the region. Forest areas mainly consist of pine species (*Pinus halepensis, Pinus sylvestris, Pinus nigra, Pinus pinea* or *pinaster*). Furthermore, bioclimatic (altitudinal) belts exist within each region in mountain areas such as the Pyrenees along the French border or Sierra Nevada on the southern Mediterranean coast.

Due to the variety of landscapes, climate and socioeconomic conditions, three different regions – Northwest (NW), Hinterland (HL) and Mediterranean (MED) – were outlined (Fig. 1), following the criteria established by the Spanish Environmental Ministry in their annual fire reports (MAGRAMA, 2002, 2007, 2012). These regions portray homogeneous areas in terms of wildfire activity by merging entire provinces or autonomous communities and have been previously used on other recent works like Moreno et al. (2014). The spatial coverage of these regions is similar to other zoning proposals like Sousa et al. (2015) or Trigo et al. (2016), being also based on NUT3S aggregations, although they include Portugal as well. The NW region includes the autonomous communities of Galicia, Asturias, Cantabria and the Basque Country, as well as the provinces of León and Zamora. This region is located within the Eurosiberian region, excluding the Pyrenees. The HL region includes all of the autonomous communities without coastline, except for the provinces of León and Zamora (included in the NW region). This region is located in the transition boundary between the Mediterranean and Eurosiberian regions, thus sharing characteristics in terms of climate influence and plant species. Finally, the MED region, situated within the Mediterranean biogeographical region, includes all the autonomous communities along the Mediterranean coast.

2.1 Fire data

Fire records from 1974 to 2013 were collected from the EGIF database and fire count data, the size of the total burned area, ignition triggering date and fire cause were retrieved for each fire event, later summarized by season at NUTS3 level. Only information on fires larger than 1 ha was retained because small fires (i.e. fires with less than 1 ha affected) were not fully compiled until 1988. This is a well-known issue affecting other regions in the Mediterranean as Portugal (Pereira et al., 2011). Additionally, it is important to remember that in the case of the autonomous community of Navarre, fire data were only available from 1988. Hence, all the analyses conducted in Navarre were based on a slightly different study period (1988–2013).

In addition to NUTS3 level, we also included a regional scale of aggregation, together with two different fire seasons. Thus, annual data were split into a spring–summer season (S) from April to September and an autumn–winter season (W) from October to March. From all available fire data information (see Table 1), eight fire features were then constructed for each fire season, NUTS and region:

- Number of fires (N): total number of events, regardless of size or ignition source.
- Burned area size (B): total fire affected area, regardless of size or ignition source.
- Number of large fires (N500): number of fires above 500 ha burned, regardless of ignition source.
- Burned area from large fires (B500): overall affected area from fires above 500 ha, regardless of ignition source.
- Number of natural fires (NL): number of fires triggered by lightning.
- Burned area from natural fires (BL): overall burned area from fires triggered by lightning.
- Number of human fires (NH): number of fires triggered by an anthropogenic source.
- Burned area from human fires (BH): overall burned area from fires triggered by an anthropogenic source.

3 Methods

The methodology consisted of three stages. First, we explored changes in the temporal evolution of fire features by means of the Pettitt test and change detection procedures on a regional scale. Second, a trend detection analysis was conducted using the Mann–Kendall (MK) test and the Sen's slope (SS) at regional and NUTS3 level. The third stage used a principal component analysis (PCA) to assess potential relationships among trends in fire features at NUTS3 level.

Statistical analyses, plotting and mapping were carried out using the R statistical software (R Core Team, 2016), packages *changepoint* and *trend* for change point analysis, *kendall* and *zyp* for trend analysis and *ggplot2* for plotting and mapping the final results.

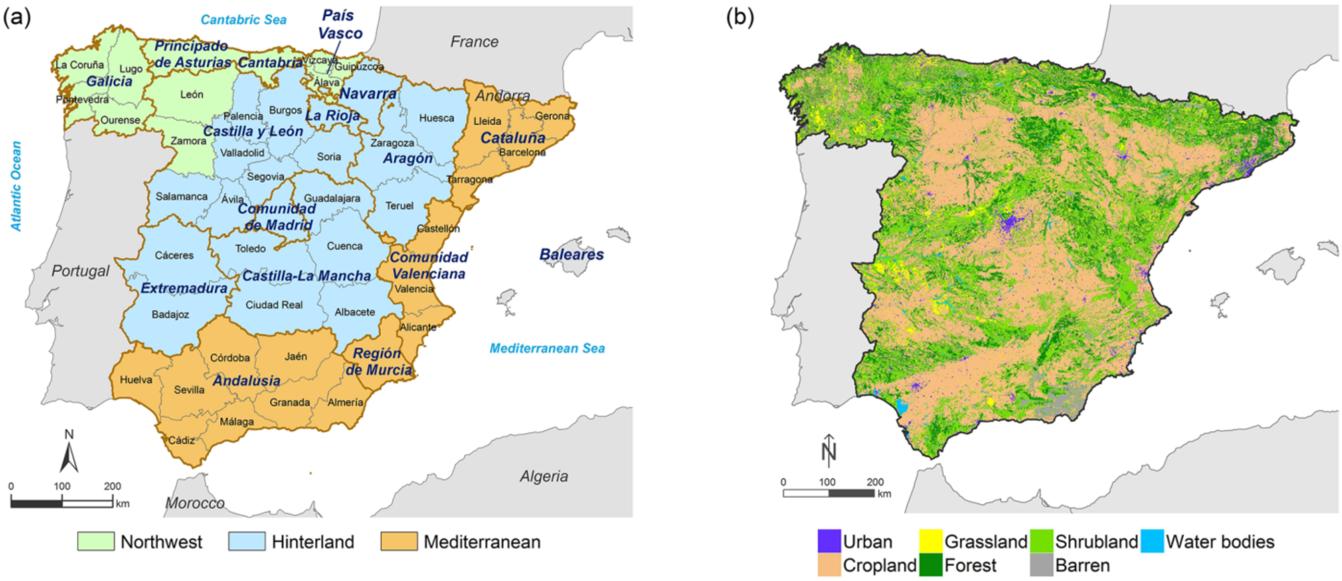

Figure 1. Spatial distribution of the three regions (Northwest, Hinterland and Mediterranean), NUTS3 and NUTS2 units in mainland Spain **(a)** and generalized land cover from CLC 2006 **(b)**.

Table 1. Statistical summary of fire regime features 1974–2013. S: spring–summer; W: autumn–winter. In parentheses, the first value corresponds to inter-region percentage and the second value to intra-region percentage. Burned area data expressed in square kilometres.

Region	Season	N	N500	NL	NH	B	B500	BL	BH
NW	S	100 232	503	1445	69 305	21 864	4874	486	14 568
		(40) (60.4)	(29.2) (79.1)	(26.9) (96.5)	(39.6) (57.4)	(33.7) (69.3)	(19.7) (79.3)	(12.2) (98.6)	(33.4) (65.6)
	W	65 826	133	53	51 355	9708	1270	7	7627
		(26.2) (39.6)	(7.7) (20.9)	(0.9) (3.5)	(29.4) (42.6)	(15) (30.7)	(5.1) (20.7)	(0.2) (1.4)	(17.5) (34.4)
HL	S	35 061	482	2593	21 048	13 307	6647	1771	7863
		(13.9) (72.3)	(27.9) (96.6)	(48.2) (99.2)	(12) (67.1)	(20.5) (89.3)	(27) (97.5)	(44.6) (99.9)	(18) (86.7)
	W	13 410	17	22	10 329	1587	171	1	1207
		(5.3) (27.7)	(1) (3.4)	(0.4) (0.8)	(5.9) (32.9)	(2.4) (10.7)	(0.7) (2.5)	(0) (0.1)	(2.8) (13.3)
MED	S	28 529	516	1230	17 598	16 146	10 771	1685	10 865
		(11.4) (78.5)	(29.9) (87.5)	(22.9) (97.2)	(10.1) (77.1)	(25) (87.9)	(43.6) (91.7)	(42.5) (98.9)	(24.8) (87.6)
	W	7820	74	36	5238	2215	971	19	1531
		(3.2) (21.5)	(4.3) (12.5)	(0.7) (2.8)	(3) (22.9)	(3.4) (12.1)	(3.9) (8.3)	(0.5) (1.1)	(3.5) (12.4)
Total		250 878	1725	5379	174 873	64 827	24 704	3969	43 661

3.1 Change point detection

Change detection or change point detection aimed to identify times when the probability distribution of a time series changes. In order to identify change points in our time series we used four different tests.

First we used the Pettitt test, a non-parametric method commonly applied to detect a single change-point in hydrological or climate series with continuous data (Pettitt, 1979). It tests the H_0 (no change) against the alternative H_1 (a change point exists). One of the advantages of this technique is its robustness to deal with outliers. In the context of wildfire science, the Pettitt test has previously been applied to detect fire regime shifts as a consequence of policy and socioeconomic development in Pezzatti et al. (2013) and Moreno et al. (2014).

The Pettitt test is calculated using the following equation:

$$UtT = \sum\nolimits_{i=1}^{t} \sum\nolimits_{j=t+1}^{T} \operatorname{sgn}(Xi - Xj), \tag{1}$$

where $\operatorname{sgn}(X) = 1$ for $X > 0$, 0 for $X = 0$ and -1 for $X < 0$, and T is the length of the time series in years. The probability of a significant change existing is calculated as follows:

$$p(t) = 1 - \exp\left(\frac{-6 \cdot U_{t \cdot T}^2}{T^3 + T^2}\right), \tag{2}$$

where $|U_{t,T}|$ reaches the maximum value where the most significant change point is found (Pettitt, 1979). This methodology allows for the identification of the most probable change point in the period examined, in each fire feature by region and season. A specific function has been developed in R environment to calculate the change point using the Pettitt approach.

As an alternative method to the Pettitt test, three additional algorithms were applied; more specifically, the *cpt.meanvar* method to identify changes in mean and variance, calculating the optimal positioning of a change point for the input data (Chen and Gupta, 2000):

– AMOC (at most one change) method is the simplest expression of the change detection algorithms from the *changepoint* package. It can detect a single change point (Hinkley, 1970), much the same as the Pettitt test.

– PELT (pruned exact linear time) is one of the most widely used methods for change point detection. It can detect multiple change points in large data sets (Killick et al., 2012), unlike the Pettitt test or AMOC. It includes an enhanced optimal partitioning, leading to a substantially more accurate segmentation. This ensures minimum change point detection in a time series, regardless of the applied penalty value. Thus, PELT is known as a more precise algorithm, usually outperforming other methods such as binary segmentation. The CROPS (changepoints for a range of penalties) penalizing type was selected. The lower the pen.value is, the higher the numbers of change points detected. For this reason, we chose many different minimum pen.values, in order to find at least one, or no more than two, breakpoints. One of the advantages of this last option is that continuous false change points were avoided commonly found at the beginning/end of the time series (for example, many cases with AMOC algorithm).

– BinSeg (binary segmentation) is an effective method for multiple change point detection (Scott and Knott, 1974). It searches for the first significant change point in a sequence, then breaks the original sequence into two subsequences: before and after the first significant change point. The procedure tests the two sub-sequences separately for a change point, with the process repeated until no further sub-sequences have change points (Chen and Wang, 2009). In our case, we previously defined a possible change point limited in 1 ($Q = 1$), to obtain only the most significant. To this end, the default penalty parameter MBIC (modified Bayes information criterion penalty) was chosen, which has proved to reduce overestimation in the number of change points and often detects the correct model (Bogdan et al., 2008). Therefore, there is no need to select a penalty value; hence in all the cases, this value is automatically established as 14.8.

3.2 Trend analysis

Change detection procedures determine if and when a certain feature has undergone a significant change across the study period. However, does it imply an increase or decrease in the values of that feature? Moreover, how strong is that change? Is the change stationary or does it vary over space? To answer all these questions, we used a trend detection procedure combining the MK and SS.

MK is a non-parametric statistical test appropriate for identifying trends in time series of data (Kendall, 1975; Mann, 1945). It is suitable 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 non-existence and existence of a trend in the time series of the observational data, respectively. Previous studies by San-Miguel-Ayanz et al. (2012) and Rodrigues et al. (2013) support the use of MK in the context of wildfire science. MK main outputs are the τ value and its associated significance level (p value). τ can be used to determine the sign of the trend, i.e. upward ($\tau > 0$) or downward ($\tau < 0$). Trends are considered significant when p value < 0.05. To facilitate the interpretation of MK outcomes, we calculated an aggregated parameter combining the τ and p value, the so-called "signed p value". It combines information on both sign and significance, calculated as the multiplication of the significance level either by 1 when $\tau > 0$ or by -1 when $\tau < 0$.

The magnitude of the change was subsequently assessed by means of the SS (Sen, 1968), a non-parametric alternative for estimating the median slope joining all possible pairs of observations, which enables a comparison of the magnitude of the detected trends. Both MK and SS were calculated for all fire features by region and NUTS3 level and for both seasons.

3.3 Principal component analysis and mapping

Finally, PCA was carried out on Sen's slope's values in order to synthesize the detected changes. PCA is a widely used technique for summarizing a large set of variables into fewer and common factors, reducing the variance of the original data. Representative principal components (PCs) were selected using the Kaiser criterion (Kaiser, 1960), which only retains PCs with eigenvalues greater than 1. In turn, the varimax rotation (VR) method was applied to identify key trends. VR transforms the selected PC, maximizing the sum of the variance and thus obtaining higher coefficients or near to zero with fewer intermediate values. The objective is to link each variable to one maximum PC to make interpretation of PCA results easier (Horst, 1965; Kaiser, 1958).

Furthermore, we summarized the temporal behaviour retrieved from PCs on an additional map. Eigenvalues from PCs 1 and 2 were classified into four categories according to their sign (positive or negative trends) and significance level (above (significant) or below (non-significant)) a 90 % con-

Table 2. Change points for AMOC (at most one change), BinSeg (binary segmentation), PELT (pruned exact linear time) methods and Pettitt test (* significant changes p value < 0.05) by fire feature, region and season from the period 1974–2013. Bold features indicate matching probable changes in at least three methods. NW is Northwest, HL is Hinterland and MED is the Mediterranean. See Sect. 2.1 for acronyms and description of fire features.

	NW				HL				MED			
	Summer				Summer				Summer			
	AMOC	BinSeg	PELT	Pettitt	AMOC	BinSeg	PELT	Pettitt	AMOC	BinSeg	PELT	Pettitt
N	**–**	**2006**	**2000, 2006**	**2005**	–	1977	1977	1983	**1994**	**1994**	**1994**	**1994***
B	**–**	**1990**	**1990**	**1991***	–	1977	1977	1991	**–**	**1994**	**1994**	**1994***
N500	–	2006	2006, 2008	1990	**–**	**1991**	**1981, 1983, 1991**	**1991**	**1994**	**1994**	**1995, 1997**	**1994***
B500	–	2006	2006, 2008, 2010	1991	–	1977	1977	1991	**–**	**1994**	**1992, 1994**	**1994***
NL	–	2006	1982, 1984	1988*	–	2006	1980, 2006	1980	2011	1994	2011	1996
BL	–	2006	2006, 2010	1988	–	1990	1990	1995	**1995**	**1994**	**1994**	**1994**
NH	–	1976	2000, 2006	2006	–	1977	1977	1997*	–	2005	1991, 1993	1994*
BH	–	2008	2008	1990	**–**	**1977**	**1977**	**1977**	**–**	**1994**	**1990,1994**	**1994***
	Winter				Winter				Winter			
	AMOC	BinSeg	PELT	Pettitt	AMOC	BinSeg	PELT	Pettitt	AMOC	BinSeg	PELT	Pettitt
N	**–**	**1984**	**1984**	**1987***	**–**	**1987**	**1987**	**1987***	–	2005	1995, 1997	1999
B	**–**	**1984**	**1984, 1989**	**1987***	–	1989	1989	2000	**1985**	**1985**	**1985**	**1986***
N500	–	1989	1990, 1993, 1995	1996	–	1977	1995, 2009	1989	**1984**	**1984**	**1992, 1999**	**1986***
B500	–	1984	1990, 1993	1996	–	1977	1995, 2009	1989	**1984**	**1984**	**1992, 1999**	**1986***
NL	1994	1993	2000, 2007	1993	–	1976	1976	1990	–	1977	1977	1992
BL	–	1984	2002, 2007	1993	**1990**	**1989**	**1990, 1994**	**1990**	–	1977	1977	1999
NH	**1987**	**1987**	**1987**	**1987***	**–**	**1987**	**1987**	**1987***	**–**	**2005**	**2005**	**2005**
BH	–	1984	1984	1987*	–	1989	1989	1987	**1981**	**1981**	**1981**	**1986***

fidence interval. PCs 3 and 4 were only shown when significant. In this way, we were able to outline homogeneous areas according to the observed temporal evolution.

4 Results

4.1 Change point detection

Only those cases where at least three of the methods agree in the year of change are taken as change points. Table 2 summarizes the year(s) of change obtained by the four algorithms. The majority of change points were detected between the late 1980s and the early 1990s. Change points have been detected in the MED region in N S, B, N500, B500, BL S, NH S and BH. Summer changes are consistently observed in 1994 in the MED features, whereas changes in the winter season in this region appear around in 1984–1986. Additionally, another six change points were found in the NW region in NH W in 1987, NL W in 1993 and B S in 1991 and two in N W and B W were found in 1984–1987. Finally, one change point was detected in N S, but in 2005–2006. In HL, five change points were found in N W and NH W in 1987, N500 S and BL W in 1990–1991 and finally BH S in 1977. It is important to note that some fire features in particular regions are very few, such as in HL and NW regions, which do not appear in Figs. 2 and 3.

4.2 Trends analysis

4.2.1 Region level

Table 3 summarizes the results from MK. Similar to change point analysis, the MED region stands out as the one with most significant changes. In general, the region returns mostly downward trends in all fire features, significant in all cases and seasons, except NL, NH and BH during winter. Only a few features underwent a trend either way in the NW region. Significant upward trends were detected in N, B, NH and BH. In all cases, trends occurred during the winter season. Significant downward trends were found in B and B500 during summer. Again, HL is the region with fewest significant trends. Overall, human-related features (NH and BH) show significant upward trends in summer and winter, whereas N increases during winter.

4.2.2 NUTS3 level

Trend detection analysis at NUTS3/provincial level combines MK and SS values. Maps in Fig. 4 summarize the results of this section. Every single map displays the results for a given fire feature. The overall value of the feature, i.e. total number of fires, burnt area and number of human-caused fires, is represented by symbol (circle) size. The colour of the circle indicates whether the MK test denotes a significant trend or not. Grey circles represent non-significant trends, whereas coloured symbols denote significant trends. For the

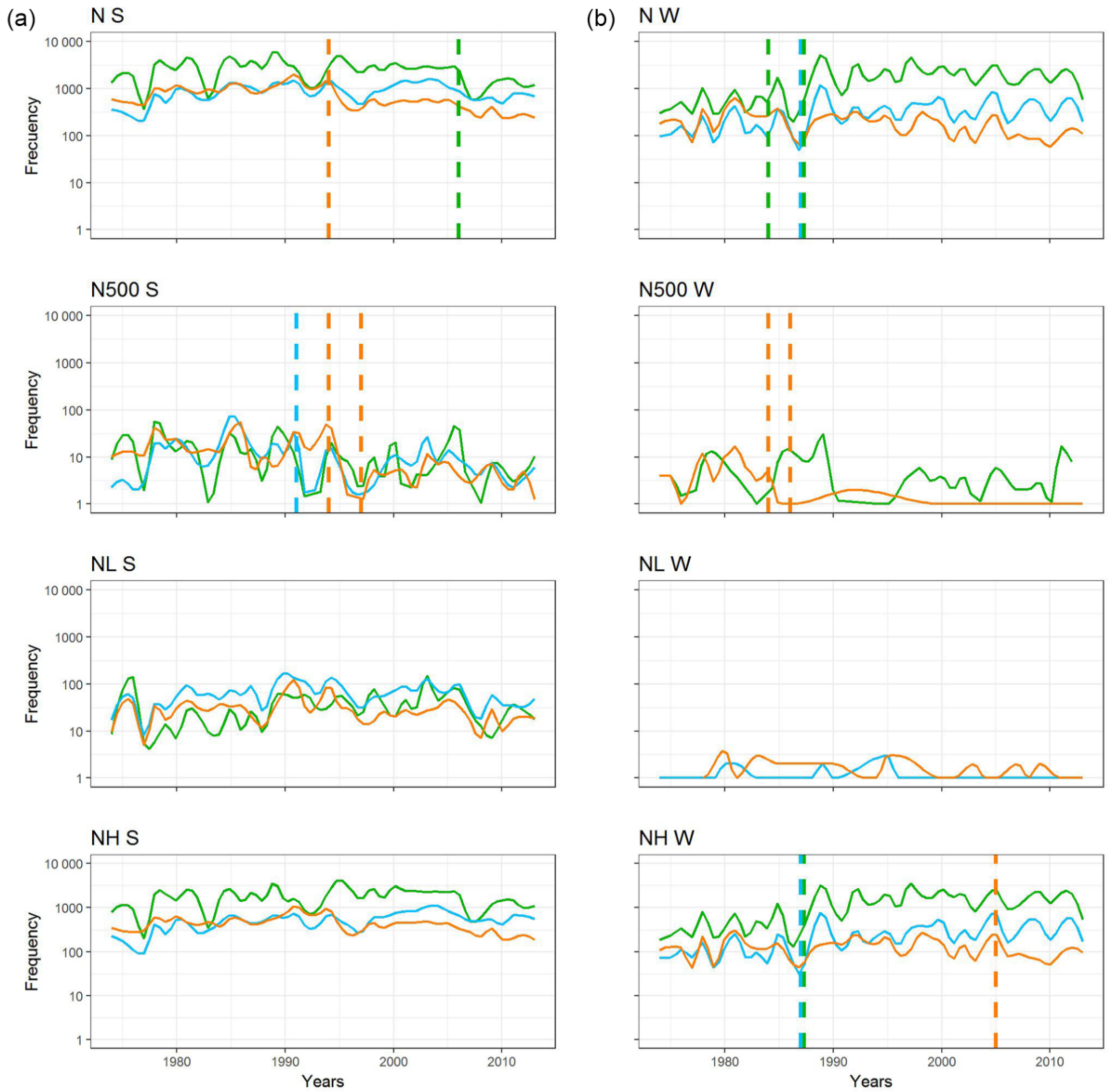

Figure 2. Detected change points and temporal evolution of fire frequency features (log scale) for the period 1974–2013 in the three regions examined: Northwest is indicated by the green line, Hinterland by the light blue line and the Mediterranean by the orange line. Column **(a)** refers to the summer season, while **(b)** is winter. Dashed vertical lines represent probable change points. See Sect. 2.1 for acronyms and description of fire features.

significant trends, the value of the SS is plotted inside the circle. We used a gree–yellow–red colour ramp to represent both the sign of the trend (negative in green and positive in red) and the trend magnitude according to the SS value.

Observing the spatial distribution of significant trends, an increment in N was found in provinces of the northwestern area and the western provinces of the hinterland on the border with Portugal. Similar to the results at regional level, provinces on the Mediterranean coast show a decrease in the number of fires, although some provinces in the southern region (Andalusia) do not show significant trends. However, differences in the seasonal behaviour were observed, with increasing trends found in the eastern provinces in NW. In turn, provinces with significant decreasing trends were located along the Mediterranean coast, southern Andalusia and the majority of provinces in Galicia. Winter N clearly presents an increase for most of the NW region and many areas of the HL.

This spatial distribution changes slightly for total B and summer B compared to those observed in N, being more visible in the northwestern area (Galicia and Asturias) and large part of Andalusia, where negative trends play a decisive role at the expense of positive trends. However, NH shows more increases across the territory, except the Mediterranean coast. However, with BH, decreases are more evident, mainly con-

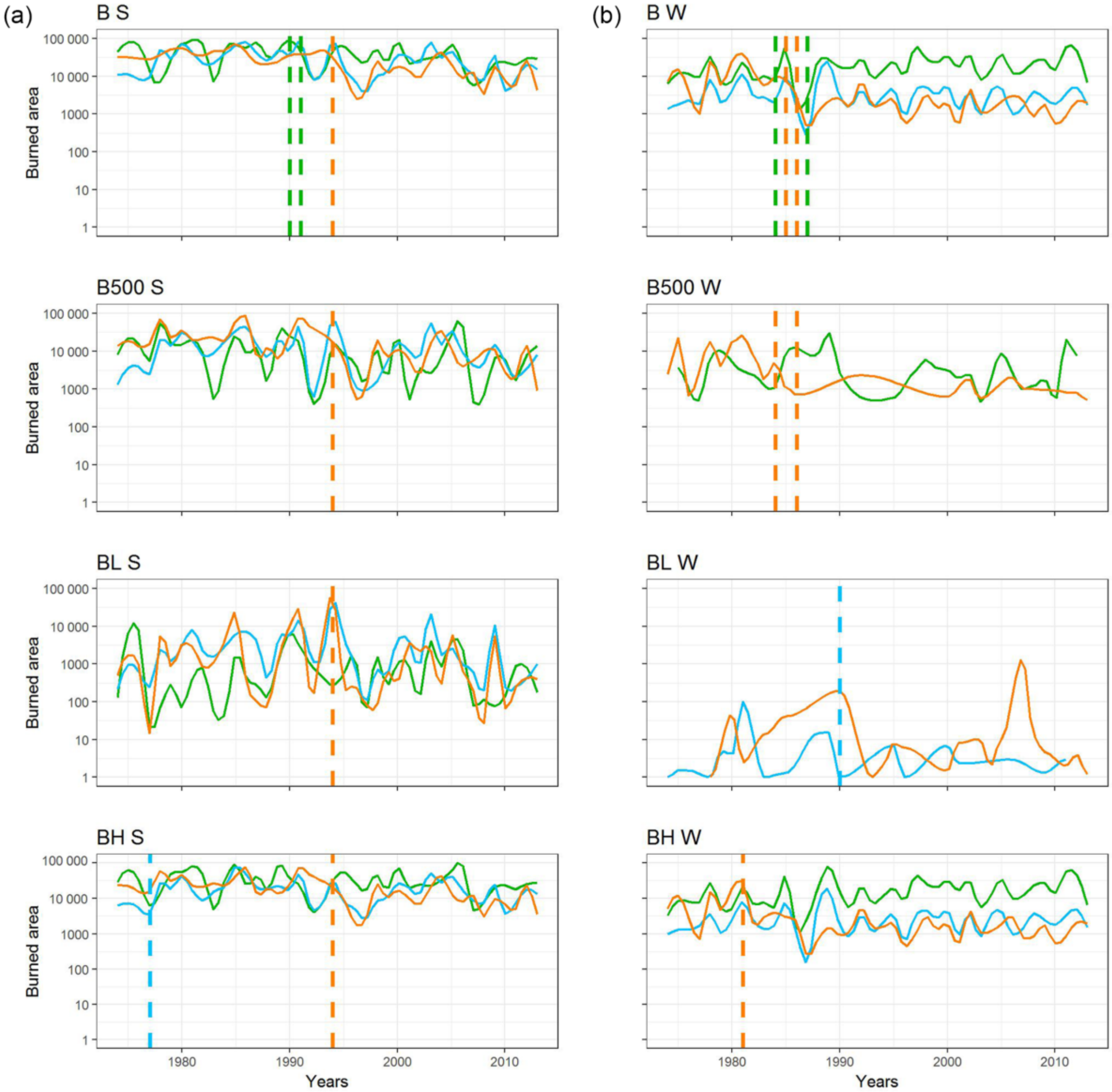

Figure 3. Detected change points and temporal evolution of burned area features (log scale) for the period 1974–2013 in the three regions examined: Northwest is indicated by the green line, Hinterland by the light blue line and the Mediterranean by the orange line. Column **(a)** refers to the summer season, while **(b)** is winter. Dashed vertical lines represent probable change points. See Sect. 2.1 for acronyms and description of fire features.

centrated in the northeast coastal areas, some provinces of the northwest and Andalusia.

The spatial distribution of SS values across mainland Spain reveals a high spatial variability in trend magnitude. The strongest trends according their standard deviation ($SD < -1.64$) or ($SD > 1.64$) were found in the NW area, both positive and negative. Strong positive trends were identified in winter fire features relating to frequency, such as total N and N–NH, but also with burned areas, as with B and BH. In contrast, the main negative trends were located again in the NW region for some summer fire features like N, B, NH and BH. In addition, the rest of the territory is covered by intermediate values, mainly in total N and B, B S, N W and NH. However, in most areas moderate negative trends play a major role (especially in the Mediterranean coast) whereas moderate positive dynamics are concentrated in the western provinces of hinterland.

4.3 Principal component analysis and varimax rotation

PCA was applied to SS values. Results from PCA provide an overview of the most relevant links among trends in fire features. According to the Kaiser criterion, 4 components (representing 88 % of the variance) out of the initial 14 were selected. Consequently, VR was only calculated for those four PCs. According to PCA eigenvalues (Table 4), PC1 (38 %

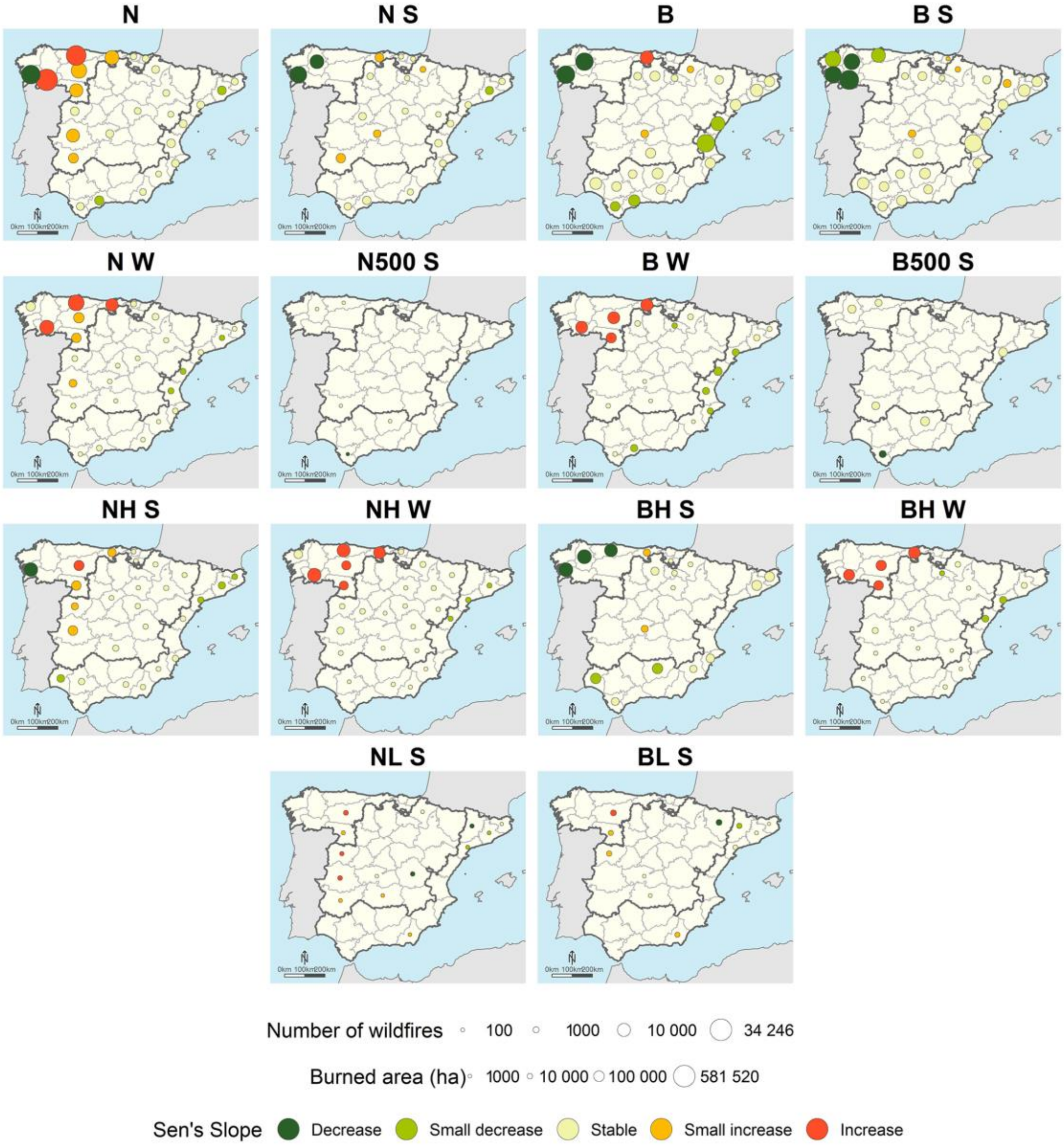

Figure 4. Spatial distribution of selected significant Sen's slope (SS) values from 1974 to -2013 according to Mann–Kendall. SS classes are based on the following intervals: decrease (< -1.6), small decrease (-1.6; -0.5), stable (-0.5; 0.5), small increase (0.5; 1.6) and increase (> 1.6). Proportional symbols represent the number of wildfires and burned area value. SS value is displayed in colour using standard deviation intervals. Provinces without symbols represent non-significant trends according Mann–Kendall test. See Sect. 2.1 for acronyms and description of fire features.

of the variance) is associated with changes in fire frequency, particularly the number of fires and human-caused fires during winter. PC1 gathers N (0.44), N W (0.52) and NH W (0.45). PC2 (27 % of the variance) relates to the fire-affected area. B (0.47), B S (0.44), BH S (0.44) and N S (0.43), suggest that burned area trends are mainly related to summer human dynamics and a slight increase in summer fire frequency. Large fire trends are noticeably isolated in PC3 (15 % of the variance in terms of both frequency and burned area). Finally, PC4 (8 % of the variance) separates natural fires dynamics in the same way as large ones fall into PC3. In general, PC1 relates to winter fire frequency, PC2 to summer burnt area, PC3 to large fires and PC4 to natural fires.

Figure 5 displays PC values at NUTS3 level. The NW and, to a lesser extent, MED regions show the highest magnitude of change when looking at the four PCs in the same picture. PC1 displays both the highest and lowest values in the NW region, although some provinces in the northeast area of the Mediterranean also show low values. PC2 shows higher values over the HL region and lower in the western area of NW. Lower values were observed for PC3 in some provinces of the Ebro Valley and others, such as Valencia, Cádiz and Ourense. In contrast, some provinces in the western NW show moderately increased values (especially in León). However, PC4, which represents naturally caused fires, exhibits intermediate positive values all over the study region, especially some provinces in the hinterland of the NW region, Valencia and Cádiz. Finally, the main negative values are located in several provinces on the Cantabrian (north) coast and the central Pyrenees (Huesca).

Figure 6 displays the summary of PCA. Increased fire frequency was observed only in the NW region, in the inland provinces of León, Zamora and Ourense, as well as in the Cantabrian cornice. Nevertheless, the burnt area decreased throughout the region. A significant winter frequency decrease was solely found in Pontevedra. However, a non-significant winter frequency decrease was observed along the Mediterranean coast and most of the interior of the country. In these latter areas, an increased summer burnt area was also observed. In contrast, a significant decrease in the summer burnt area was only detected in the Galician provinces (NW). In addition, significant trends in large or natural fires were found in the three regions. Increased lightning fire activity was observed in León and Zamora (NW) and Valencia (MED). Lesser natural fire activity was detected in Asturias (NW) and Huesca (HL). In turn, the occurrence of large fires was more frequent in León and Pontevedra (NW), whereas the opposite could be found in Ourense (NW), Huesca (HL) and Valencia (MED).

5 Discussion

In this paper, we present an analysis of spatial–temporal trends of several fire regime features at different scales for mainland Spain. Various statistical methods for time series were applied to historical fire data to (i) explore the temporal behaviour of fire features and (ii) investigate key relationships in trends, with the end purpose of the research being to improve the definition of fire regime. It should be noted that the analysis is based on historical fire records, and thus there are some limitations related to landscape-level fuel build-up that cannot be addressed.

Change detection procedures suggest the existence of change points in several fire features (Table 2). Changes were mostly found in the Mediterranean region from the late 1980s to the first half of the 1990s. Moreno et al. (2014) support our findings for number of fires and burned area on a seasonal scale, and they also found similar change points using the Pettitt test on a stepwise approach with an 11-year moving window. This work is a particularly good match for our objective because the same regions and fire data from the EGIF database were used, although the study period was slightly different (1968–2010) and only examined number of fires and burnt area. In particular, these authors observed downward changes starting from the 1990s to the present in the Mediterranean region for both winter and summer and in the summer of Northwest and Hinterland, which are in line with our findings (see Fig. 2). They concluded that climate might have played a role in the change points of the Mediterranean region (mid-1980s and 1990s) and the Northwest region (1991). In addition, the change points we detected in the Northwest region for the number of winter fires (Fig. 2) might be linked to different causes, such as rising population density, agricultural activities and more cases of arson, as Moreno et al. (2014) have pointed out. However, increased investment in fire suppression might have played a role in reducing the burned area (Seijo and Gray, 2012). However, this is a difficult aspect; in this sense the analysis in the northern region of Portugal (Fernandes et al., 2014) found that the shift towards decreasing area burned did not happen in areas with unsuccessful/insufficient fire-fighting efforts.

Overall, all methods detect significant changes in some fire features in the Mediterranean and the Northwest regions during both seasons, although slight differences in the reported year do exist.

We considered it necessary to assess other fire regime features, such as large fires and fire sources. The inclusion of trends in large fires is justified because of their remarkable socioeconomic and natural impact (Alvarado et al., 1998; San-Miguel-Ayanz et al., 2013). Change detection suggests that the number of large fires has changed since the mid-1990s throughout the Mediterranean (see Fig. 2), supported by findings from MK, which detects a decrease in frequency and affected area (Table 3). Cardil and Molina (2013) report similar changes, although these authors have taken large fires to be those burning more than 100 ha and have excluded some provinces from their assessment. They and others, like Brotons et al. (2013) and Ruffault and Mouillot (2015), suggest that large fires have decreased because extinguishing methods have improved, again, mainly due to the extraordinary investment that Spain has devoted to fire suppression.

Findings from change detection are supported and completed by those from trend analysis. At a regional level, the Mediterranean region shows a negative trend in the majority of fire features (see Table 3). The Northwest and Hinterland share a positive trend during winter. Number of fires presents a general downward trend in both seasons in the Mediterranean and during summer in Northwest. In the case of the Hinterland region, the trend in the number of fires suggests a higher frequency in winter. This behaviour was also found by Zavala et al. (2011) and Turco et al. (2016). The latter found an apparent shift in the mid-1980s, the same as we detected. Among the feasible causes that may explain this spatial contrast, we found factors such as land use changes caused by land abandonment leading to vegetation recovery during recent years (Bonet and Pausas, 2007; Castellnou et al., 2010), resulting in an accumulation of fuels. However, the burned area shows a decrease in all regions and seasons. Previous studies by Rodrigues et al. (2013), Spano et al. (2014) and Turco et al. (2016) have also found negative trends for a very similar time span. These works sug-

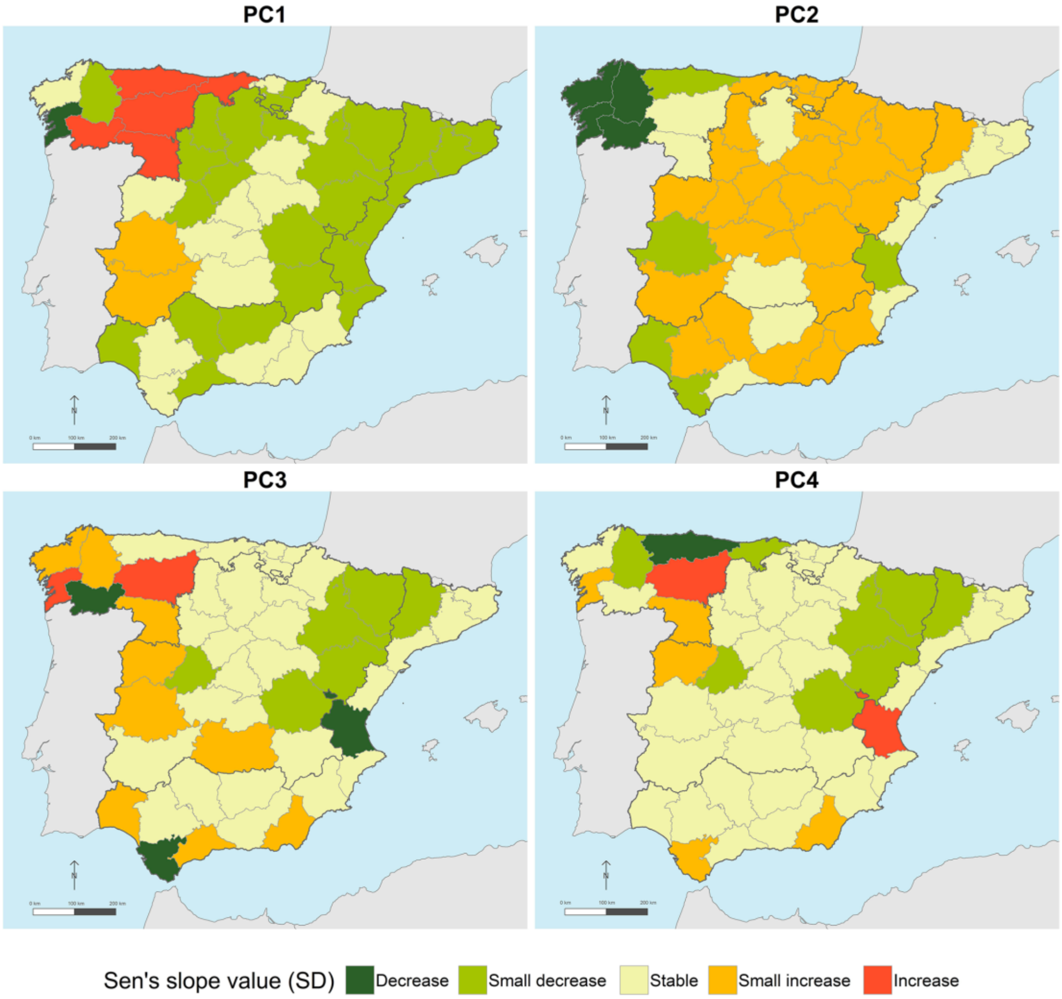

Figure 5. Spatial distribution of the principal component coefficients of Sen's slope, 1974–2013. Values represented using standard deviation intervals. Sen's slope classes are based on the following intervals: decrease (< -2.5), small decrease (-2.5; -0.5), stable (-0.5; 0.5), small increase (0.5; 2.5) and increase (> 2.5).

Table 3. Signed p value of Mann–Kendall test in the period 1974–2013 by fire feature, season and region. Values in bold correspond to significant trends (p value < 0.05), with their corresponding symbol + or – for positive or negative trends, respectively. NW is the Northwest; HL is the Hinterland; MED is the Mediterranean region. See Sect. 2.1 for acronyms and description of fire features.

	N		N500		NL		NH	
	S	W	S	W	S	W	S	W
NW	− (0.14)	+ **(0.01)**	− **(0.03)**	+ (0.26)	+ (0.14)	− (0.49)	+ (0.77)	+ **(0.01)**
HL	+ (0.21)	+ **(0.01)**	− (0.22)	− (0.39)	+ (0.62)	− **(0.03)**	+ **(0.01)**	+ **(0.01)**
MED	− **(0.01)**	− **(0.01)**	− **(0.01)**	− **(0.01)**	− (0.11)	+ (0.13)	− **(0.01)**	− (0.54)
	B		B500		BL		BH	
	S	W	S	W	S	W	S	W
NW	− **(0.01)**	+ **(0.03)**	− (0.13)	+ (0.41)	+ (0.68)	− (0.28)	− (0.13)	+ **(0.01)**
HL	− (0.25)	− (0.95)	+ (0.51)	− (0.48)	− (0.44)	− (0.08)	+ (0.84)	+ (0.84)
MED	− **(0.01)**	− **(0.01)**	− **(0.01)**	− **(0.01)**	− (0.22)	+ (0.06)	− **(0.01)**	+ **(0.01)**

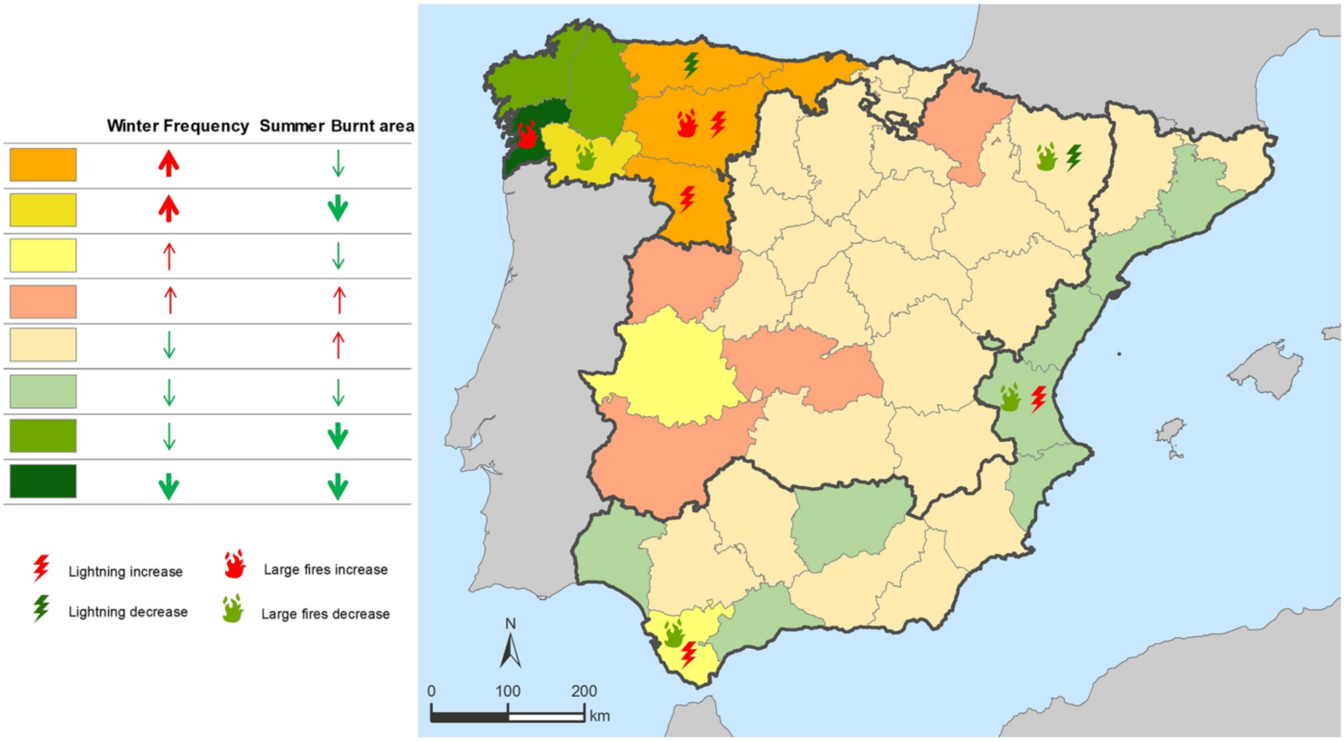

Figure 6. Summary of spatial–temporal behaviour from principal component analysis. Thick arrows mean significant trends, and thin ones are non-significant trends according to 90 % confidence interval.

Table 4. Varimax rotation correlation values, standard deviation (SD) and variance (VAR) from principal component analysis on Sen's slope results, 1974–2013. The most meaningful features (correlation > 0.43 or < −0.43) are marked bold. See Sect. 2.1 for acronyms and description of fire features.

		PC1	PC2	PC3	PC4
SD		2.3	1.95	1.47	1.07
VAR		0.38	0.27	0.15	0.08
Fire feature	N	**0.44**	0.23		−0.14
	N S	0.18	**0.43**		−0.11
	N W	**0.52**	0.11	−0.10	
	B		**0.47**		
	B S	−0.18	**0.44**	0.11	
	B W	0.35			0.21
	N500 S			**0.63**	
	B500 S			**0.69**	
	NL S				**0.60**
	BL S				**0.60**
	NH S	0.19	0.36	−0.17	0.12
	NH W	**0.45**			
	BH S	−0.20	**0.44**	−0.14	0.27
	BH W	0.27		−0.14	0.29

gest that the decrease might be explained by recent improvements in management of wildfires and monitoring systems. Additionally, the European Forest Fire Information System (EFFIS) observed a clear downward trend in the total burnt area in some southern European countries (including Spain) after 1990, partly due to improved fire protection services (Schmuck et al., 2010). Nevertheless, the Northwest region during winter emerges as the sole exception, with the affected area showing an upward trend. It can be argued that a persistent increase in arson has tended to extend the surface affected in this area (Ganteaume et al., 2013). Finally, positive trends are detected in winter in the number of human fires in the Northwest and Hinterland regions (both summer and winter), contrasting with a decrease found in the Mediterranean region. Human-burnt area follows a positive trend mainly during winter in the Northwest and in many areas in the south, whereas during summer a decrease is more widespread. This fact suggests that summer human-burnt area is declining, but intensifies during winter. The reasons which may explain this fact could relate to a continuance of arson attacks as a common practice which still remains. To our knowledge, this is the first analysis of fire frequency and burned area based on the source of the fire. Therefore, we cannot establish any comparison.

Downscaling to NUTS3/provincial level, Sen's slope has exposed the underlying spatial heterogeneity in the magnitude of the trends, both positive and negative (Fig. 4). In this respect, number of fires is the feature with the highest degree of change. Trend magnitude in the number of fires appears to be distributed along a west-to-east gradient, starting with increasing dynamics in the west and ending with downward trends in the eastern Mediterranean provinces. In contrast, the sharpest decreases are observed in features relating to burned areas such as burned area, burnt area during summer and human-burnt area during summer. However, this behaviour is reversed during winter, although trend magnitude is less marked. This is probably due to the improvement in fire extinguishing or encouraging monitoring and prevention (MAPA, 1988; Rodrigues et al., 2016), particularly encouraged during summer. Fires ignited by lightning perhaps show the most contrast as there is a marked dichotomy between west and northeast. For instance, decreasing dynamics are found in the northeast area, whereas major upward trends are situated in the western half of the region, which is considered one of the most lightning-ignition-prone areas of Spain (Ortega et al., 2012). According to our results, there seems to be increased fire activity from natural causes. However, trends are more noticeable in the number of natural fires than in natural burned area, thus the average size of lightning-caused fires seems to be shrinking. It is important to note that other seasonal partitions like those reported by Moreno et al. (2014), Sousa et al. (2015) and Trigo et al. (2016) have been explored, finding almost no differences.

Finally, PCA–VR enables trends to be grouped to provide an easily readable description and characterization of fire regime at provincial level, also clarifying the spatial pattern of key fire trends. Therefore, we extracted four main components (see Table 4, Figs. 5 and 6), i.e. four distinct temporal behaviours: winter fire frequency (PC1), summer burnt area (PC2), large fires (PC3) and natural fires (PC4). The first two components are associated with seasonal fire activity, whereas components 3 and 4 relate to intrinsic characteristics of wildfires, such as fire size and ignition source, respectively. PC1 has led to identifying winter frequency trends and human-caused frequency during winter as key trend features, while PC2 gathers trends from burned area features, but mostly summer trends (burned area and human-burnt area), indicating that summer fire dynamics might play a secondary role compared to winter, at least in terms of the strongest temporal trend. However, the last two PCs, large fires and natural fires trends, appear to be similarly important. In addition, a seasonal contrast is clearly evident between the Northwest region dynamics and the rest of mainland Spain (i.e. negative trends located mainly in Galicia).

6 Conclusions and future work

In this paper, we have explored spatial–temporal changes of several fire regime features in Spain at regional and provincial levels. To this end, we combined change point detection techniques, trend detection procedures and PCA, applied to fire data from 1974 to 2013. Our results suggest that two main trends based on seasonal differences can be distinguished: fire frequency during winter and burned area during summer. It is important to highlight that in both cases human cause is strongly correlated to the trends, and thus apparently changes in burned area and fire frequency are partially controlled by human-caused fires. Additionally, mapping SS and PCA results at NUTS3 level suggests different behaviour in the northwestern provinces, which return the highest values, in terms of both frequency (upward trends) and burnt area (downward trends).

Change detection suggests a main breakpoint in the temporal evolution of fire features around the late 1980s and in the first half of the 1990s. In contrast, the Mann–Kendall test on a regional scale has revealed that the Mediterranean region presents a high degree of negative trends in the majority of fire features, in contrast to the Hinterland and Northwest. According to Sen's slope, the main trends at NUTS3 level show high spatial–seasonal variability, and several trend gradients linked to the number of fires and naturally caused fires were detected. In this regard, overall fire frequency shows an upward tendency, particularly strong during winter, while the burned area exhibited a general downward trend.

The analysis of spatial–temporal trends opens new research lines. For instance, further evaluation is required to incorporate other benchmark spatial units to provide greater detail than found at provincial level (for instance, grid cells). Nevertheless, deeper insights into causes explaining temporal behaviour of the main fire regime features should be explored, especially those linked to weather conditions and land use changes. Finally, the role of small fires ($1 < \text{ha}$) can be included, thus enriching fire regime assessment in order to avoid potential bias caused by their exclusion. In any case, the analysis given in this paper should provide a useful reference to obtain spatially and temporally explicit assessment of fire regime changes, to help improve delimitation of homogenous fire regime areas and to gain a more complete overview of wildfire phenomenon.

Data availability. Fire data are available upon request to the Spanish Ministry of Agriculture, Fisheries and Environment. CLC is freely available from the European Environmental Agengy (EEA).

Competing interests. The authors declare that they have no conflict of interest.

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6 CHAPTER 6: THE INFLUENCE OF FIRE-WEATHER ON THE EVOLUTION OF FIRE ACTIVITY

This chapter describes the results, discussion and main conclusions obtained from the analysis of spatial and temporal associations between monthly time series of fire weather danger indices (Fire Weather Index, Burning Index and Forest Fires Danger Index) at regional and local level. Decomposition of time series was the first step, then apply cross-correlation to explore seasonal associations at regional scale, as well as, a Pearson's correlation was calculated between each index and 18 fire-activity subsets by fire size and cause at local scale.

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Research article

The role of short-term weather conditions in temporal dynamics of fire regime features in mainland Spain

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ABSTRACT

In this paper we investigate spatial-temporal associations of fire weather danger and fire regime features from 1979 to 2013. We analyze monthly time series of fire activity (number of fires and burned area) and fire weather danger rating indices (Fire Weather Index, Burning Index and Forest Fire Danger Index) at two spatial scales: (i) regionally, splitting the Spanish mainland into Northwest, Hinterland and Mediterranean regions; and (ii) locally, using the EMCWF grid. All analyses are based on decomposing time series to retrieve differential indicators of seasonal cycles, temporal evolution and anomalies. At regional scale we apply lagged cross-correlation analysis (4 lags or months before fire) to explore seasonal associations; and trend detection tests on the temporal evolution component. At the local scale, we calculate Pearson correlation coefficients between each individual index and the 18 possible fire-activity subsets according to fire size (all sizes, > 1 ha and > 100 ha) and source of ignition (natural, unintended and arson); this analysis is applied to both cycles, temporal and anomalies series.

Results suggest that weather controls seasonal fire activity although it has limited influence on temporal evolution, i.e. trends. Stronger associations are detected in the number of fires in the Northwest and Hinterland regions compared to the Mediterranean, which has desynchronized from weather since 1994. Cross-correlation analysis revealed significant fire-weather associations in the Hinterland and Mediterranean, extending up to two months prior fire ignition. On the other hand, the association between temporal trends and weather is weaker, being negative along the Mediterranean and even significant in the case of burned area. The spatial disaggregation into grid cells reveals different spatial patterns across fire-activity subsets. Again, the connection at seasonal level is noticeable, especially in natural-caused fires. In turn, human-related wildfires are occasionally found independent from weather in some areas along the northern coast or the Ebro basin. In any case, this effect diminishes as the size of the fire increases. Our work suggests that for some regions of mainland Spain, these fire danger indices could provide useful information about upcoming fire activity up to two months ahead of time and this information could be used to better inform wildland fire prevention and suppression activities.

1. Introduction

Understanding the complexity and dynamics of fire regimes is growing in importance as the size and severity of wildfires increase in many regions (Falk et al., 2011). Many factors are involved when defining fire regimes; it is widely recognized the crucial role humans play in wildfire incidence (San-Miguel-Ayanz and Camiá, 2009) but it is also indisputable the remarkable influence exerted by weather and climate. Generally speaking, wildfires are the result of complex human–environment interactions and synergies (Koutsias et al., 2012; Krebs et al., 2010; Liu et al., 2012; Liu and Wimberly, 2016). The final affected area depends on the fire conducive weather, fuel availability and topography (Drobyshev et al., 2012; Parisien et al., 2011; Whitman et al., 2018), but also on fire suppression and site accessibility, thus shaping the resulting fire perimeter (Flannigan et al., 2009; Krebs et al., 2010; Papadopoulos et al., 2013; Shakesby and Doerr, 2006). Notwithstanding, weather factors influence both fire ignition and spread (Thompson et al., 2011). For instance, coincident high temperatures and extended drought circumstances may promote larger fires (Camia and Amatulli, 2009; Piñol et al., 1998; Trigo et al., 2016; Turco et al., 2014; Urbieta et al., 2015).

In Spain, several works report an overall decrease of wildfire

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frequency along the Mediterranean coastlands but an intensification in the remaining territory (Turco et al., 2016). Likewise, a recent paper by Jiménez-Ruano et al. (2017b) reported increased fire activity in the Northwest area of Spain, one of the most fire-affected regions in Europe (Koutsias et al., 2016; Pausas and Fernández-Muñoz, 2012). Furthermore, winter fires and large fires are more frequently observed, partially induced by human activities (Jiménez-Ruano et al., 2017a) but also related to the lengthening of the fire season (Jolly et al., 2015). Therefore, we can safely assume fire dynamics are, to some extent, linked to climate variability. As a matter of fact, some studies already suggest a transition towards more climate-driven fire regimes at a global scale (Pechony and Shindell, 2010) and an increased role of climate factors in fire occurrence (Rodrigues et al., 2016).

However, one of the main undefeated challenges of fire science is to ascertain the extent to which climate and human factors are influencing fire regime dynamics. In other words, what role does weather play in the evolution and temporal behavior of fire incidence? Does it depend on the source of ignition? A number of studies on wildfire incidence have focused on current climate (Abatzoglou and Williams, 2016; Bedia et al., 2013; Parente et al., 2016; Pausas, 2004; Turco et al., 2014) as well as future scenarios (Boulanger et al., 2014; Mori and Johnson, 2013; Perera and Cui, 2010); but studies examining the temporal weather-fire interactions still has room for improvement.

In this sense, a widespread approach to measure the influence of weather on wildfires has been the use of fire weather danger rating indices. The Canadian Fire Weather Index (FWI) is the most established index being applied worldwide (Van Wagner, 1987); without being exhaustive, we find examples of use of FWI in North America (Jain et al., 2017; Turetsky et al., 2004; Wang et al., 2015; Wotton et al., 2017), Europe (Dupire et al., 2017; Viegas et al., 2006), and also in Iberian Peninsula (Bedia et al., 2012). Likewise, other rating indices have been explored such as the United States Burning Index (BI) (Schoenberg et al., 2007) or the McActhur's Forest Fire Danger Index (FFDI) in Australia (Sanabria et al., 2013). However, few works compare (i.e., Nolasco and Viegas, 2006; Pérez-Sánchez et al., 2017) the performance of different fire weather indices.

In this study, we investigate the temporal association between weather factors and fire incidence, using fire weather rating indices as a proxy of short-term weather conditions. We analyze temporal correlations between monthly time series of fire weather danger indices (FWI, BI and FFDI) and fire regime features (fire frequency and burned area) in the period 1979 to 2013. Analyses were carried out at two different spatial levels; regions, splitting mainland Spain into three homogenous areas in terms of fire activity (i.e. term that refers to two variables: number of fires and total burnt area combination) and climate conditions; and at a local level, using the European Centre for Medium-Range Weather Forecasts (ECMWF) grid (0.75ºx0.75°, roughly 82 × 82 km). Time series of weather indices and fire data were decomposed (season, trend and remainder), analyzed and compared using a combination of correlation and trend detection procedures. Our main goals are (1) to determine the extent to which weather controls intra and inter-annual fluctuations of number of fires and burned area at a regional scale, and (2) to detect spatial patterns according to fire size and ignition source.

2. Materials and methods

2.1. Study area

The study area is mainland Spain (thus excluding both the Balearic and Canary archipelagos and the autonomous cities of Ceuta and Melilla). Spain is very biophysically diverse, presenting a wide variety of climatic, topographical, and environmental conditions. Mainland Spain is dominated by two biogeographical regions. The Eurosiberian region covers most of the northern area of the country. It is characterized by an Oceanic climate (according to Koeppen's climate classification - *Cfb*), mostly covered by various types of vegetation from deciduous oak (*Quercus robur, Fraxinus excelsior* or *Fagus sylvatica*) and ash to evergreen oak woodlands, but this region is also heavily dominated by forest plantations such as *Pinus radiata* and *Eucalyptus globulus*. The Mediterranean region covers the remaining territory. Hot-summer Mediterranean (*Csa*) and cold semi-arid (*BSk*) climates characterize this area, which therefore has notably drier and warmer conditions than the Eurosiberian region. These conditions, coupled to human activity, favor complex mosaics of agricultural systems and plant communities. Sclerophyllous and evergreen vegetation, such as *Quercus ilex* and thermophilous scrublands (maquis and garrigues formations), dominate the region, and forest areas mainly consist of pines (*Pinus halepensis, Pinus sylvestris, Pinus pinea or Pinus pinaster*). Furthermore, bioclimatic (altitudinal) belts exist within each region in mountain areas such as the Pyrenees along the French border or Sierra Nevada on the southern Mediterranean coast.

Due to the variety of conditions the Spanish Ministry of Agriculture and Environment outlined 3 major regions (Fig. 1) portraying homogenous fire regimes: Northwest (NW), Hinterland (HL) and Mediterranean (MED). The NW region includes the autonomous communities of Galicia, Asturias, Cantabria and the Basque Country, as well as the provinces of León and Zamora. This region is located broadly within the Eurosiberian region, excluding the Pyrenees mountain ranges. The HL region includes all of the autonomous communities without coastline, except for the provinces of León and Zamora (which belong to NW). HL is located in the transition inland between the Mediterranean and Eurosiberian regions, thus sharing climate influence and plant species from both of them. Finally, the MED region, situated completely within the Mediterranean biogeographical region, includes all the autonomous communities along the Mediterranean coastlands, as well as the western provinces of Andalusia.

2.2. Fire weather danger rating indices

We have explored 3 of the most widespread fire weather danger rating indices in the literature: the Canadian Fire Weather Index (FWI), the US Burning Index (BI) and Australian Forest Fire Danger Index (FFDI). These indices summarize weather conditions related to the 'burning potential'; nonetheless FWI and BI also reflect fuel moisture whereas FFDI is a pure meteorological index.

FWI was computed following the Van Wagner and Pickett (1985) specifications, using a specifically-written C+ + library. We used noon weather (either 12.00 or 13.00 local standard time) daily gridded data from the ECMWF Interim Reanalysis (Dee et al., 2011). The US BI parameters (fuel moistures and indices) were computed following Bradshaw et al. (1983). The final BI index represents the expected rate of spread and heat release of a given fire. Again, gridded data from the ECMWF was employed to build the index. To ensure spatial-temporal homogeneity, FWI and BI calculations were constrained to fuel model G (short needle, heavy dead), because this heavily weights long time-lag fuels, thus better representing seasonal wetting-drying cycles (Jolly et al., 2015). Finally, FFDI was calculated following the steps established by McArthur and expressed as equations by Noble et al. (1980). The Drought factor for these equations was calculated using the improved formula presented by Griffiths driven by the Keetch-Byram Drought Index, which was calculated using daily maximum temperature and precipitation from each ECMWF reanalysis dataset and mean annual precipitation values from the WorldClim climate dataset (Hijmans et al., 2005). See Jolly et al. (2015) for deeper insights on the calculation of the indices. Fig. 2 shows the overall workflow followed to calculate every index.

2.3. Fire data and fire-activity subsets

Wildfire information in the period 1979–2013 was retrieved from fire reports in the Spanish General Statistics Forest Fires database (EGIF), compiled by the Spanish Department of Defense Against Forest Fires The

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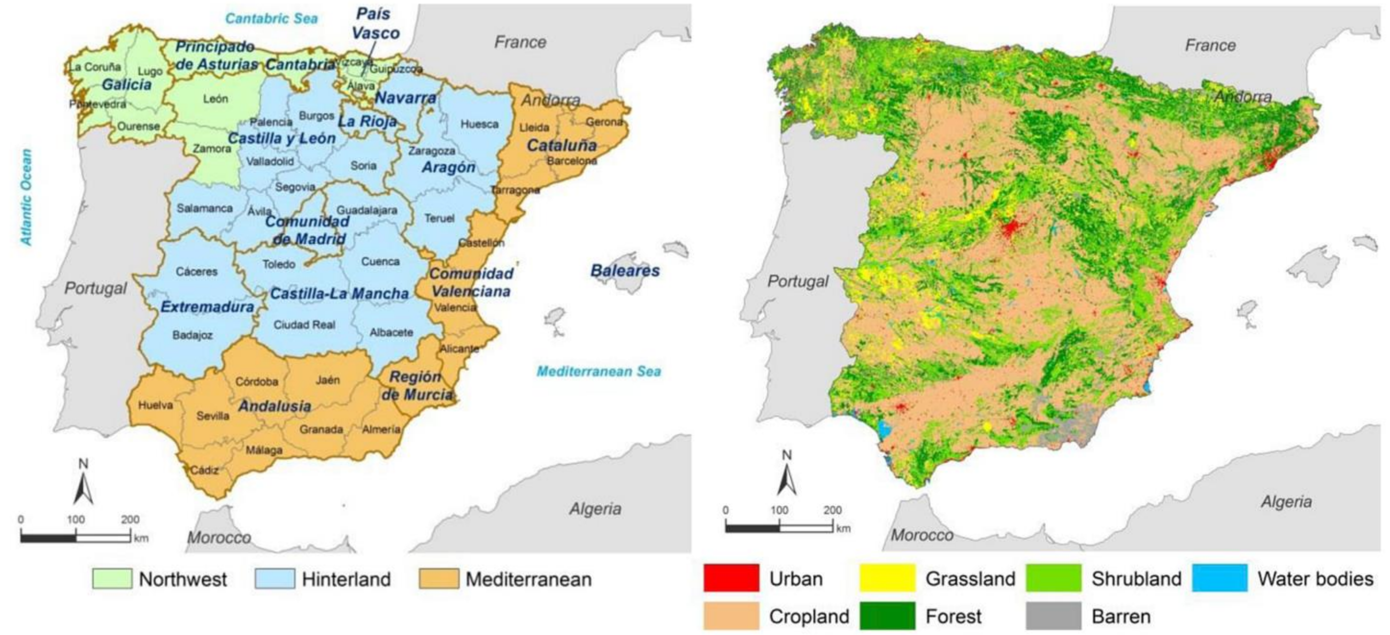

Fig. 1. Spatial distribution of the three regions considered (Northwest, Hinterland and Mediterranean), also NUTS3 and NUTS2 units in mainland Spain (left) and generalized land cover from Corine Land Cover 2006 (right).

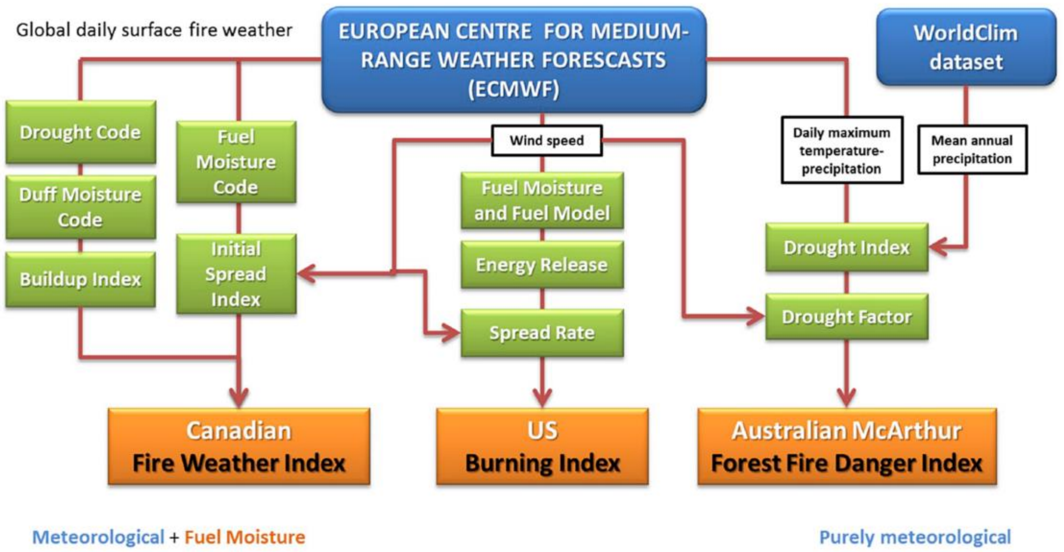

Fig. 2. Overall workflow to obtain the Fire Danger Weather Rating Indices employed in the study (see Jolly et al., 2015, for more details).

EGIF database stands out for its precision and completeness, since is one of the oldest wildfire databases in Europe, beginning in 1968 (Vélez, 2001). Among other valuable information, fire reports provide the starting point of each fire event –recorded on a 10 × 10 km reference grid–, the ignition source, the affected burned area size, and detection date.

Two sets of fire-related time series were constructed at a monthly level: the overall fire frequency (N -number of fires) and burned area (BA - total affected area in has) were summarized at a regional level (Table 1); additionally fires were assign to its corresponding ECMWF-grid (Fig. 3). Fire data was then split into several fire-activity subsets of ignition source (natural, negligence/accident and arson) and fire size (All sizes, > 1 ha and > 100 ha). Negligence and accidental fires will be further referred to as 'unintended'.

2.4. Methods

Fire-weather relationships were analyzed in 3 stages: (1) first we decompose time series of weather data and fire features; (2) then we investigate spatial-temporal associations at a regional level; finally, (3) we try to identify spatial patterns in fire-weather associations at grid level. The whole process involves several statistical procedures. We use time series decomposition to split temporal observations into its main components, cross-correlation to investigate seasonal cycles, Mann-Kendall and Sen's slope for trend detection and Pearson's correlation coefficient to explore spatial patterns of association at local level.

All statistical procedures, maps and plots were obtained using the R statistical programming language (R Core Team and R Development Team Core, 2017), packages *astsa* for cross-correlation and *trend* and Mann-Kendall and Sen's slope tests; *raster* and *rgdal* for spatial data manipulation; *stats* for Pearson's correlation analysis; and *ggplot2* for mapping and plotting.

2.4.1. Decomposing monthly time series

Time series of fire activity and weather indices were decomposed

Table 1
Number of fires and burned area summary per ignition cause and fire size globally and regionally for the period 1979–2013.

Size	Fire frequency			Burned area (ha)		
	Natural	Unintended	Arson	Natural	Unintended	Arson
			Spanish mainland (whole study area)			
All	20,336	95,607	273,043	373,971	1,175,281	2,734,781
> 1 ha	4,923	39,706	124,316	372,225	1,163,028	2,700,633
> 100 ha	348	1,521	4,601	333,684	867,602	1,628,286
			Northwest			
All	3,848	26,408	223,149	38,122	190,636	1,777,329
> 1 ha	1,308	12,142	101,116	37,673	187,120	1,748,864
> 100 ha	74	345	3,208	26,405	88,565	879,687
			Hinterland			
All	10,785	38,104	29,554	177,672	429,890	453,538
> 1 ha	2,474	15,791	14,226	176,800	425,030	450,019
> 100 ha	193	621	762	157,617	311,510	327,553
			Mediterranean			
All	5,703	31,095	20,340	158,177	554,755	503,913
> 1 ha	1,141	11,773	8,974	157,751	550,878	501,750
> 100 ha	81	555	631	149,662	467,527	421,047

using Seasonal-Trend Decomposition (STL; Cleveland et al., 1990). STL is a very versatile and robust method to divide time series allowing the detection of both gradual changes (trend) and cycles (season). More importantly, decomposing enables further analysis such as cross-correlation (CC) whose performance is affected by underlying temporal structures; hence it is strongly recommended that time series were detrended beforehand.

STL consists in a sequence of Locally Weighted Regression Smoother (LOESS) procedures that split a time series into three components: trend, season and remainder. For a detailed description of the algorithm see Cleveland et al. (1990). For the sake of comprehension, hereafter we will refer to season, trend and remainder assuming the following meaning:

- **"Season"** as the component obtained that represents exclusively the positive and negative peaks of the detected seasonal cycles within the year.
- **"Trend"** as the component extracted from the time period that only takes into account the inter-annual evolution throughout the same, disregarding seasonal cycles.
- **"Remainder"** as the component that is left over from the two

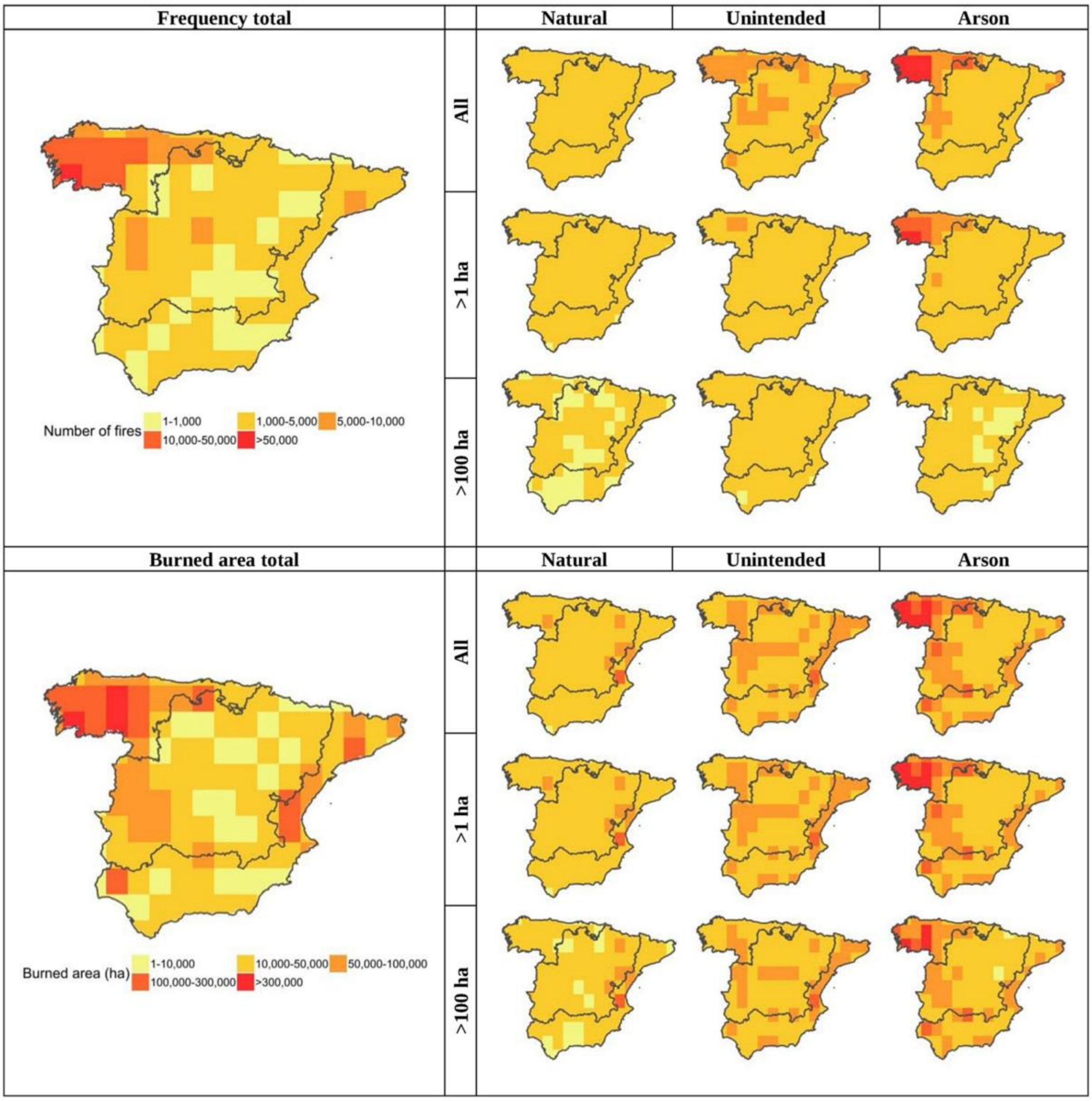

Fig. 3. Spatial distribution of total number of fires (top) and total burned area (bottom) across size-and-cause subsets.

previous ones, and which therefore can be understood as anomalies or extreme events (both exceptionally high and low values) that are outside the average values of the trend and seasonal time series.

2.4.2. Spatial-temporal associations at regional level

Our first objective was to determine the extent to which weather controls intra-annual (seasonal) fluctuations of fire activity. To answer this question we conducted a cross-correlation (CC) analysis at a regional level using the season component from STL. Cross-correlation is a standard method that estimates the degree of similarity between two discrete time sequences (x and y) as a function of the displacement (lagged or the delay in the synchrony of two temporal events) of one relative to the other (Venables and Ripley, 2002). We followed formula (1 and 2) about the definitions of the lags established by Venables and Ripley (2002) who extended to several time series observed over the same interval:

$$\gamma_{ij}(t) = \mathrm{cov}(X_i(t+T), X_j(T)) \tag{1}$$

$$c_{ij}(t) = \frac{1}{n} \sum_{s=\max(1,-t)}^{\min(n-t,n)} \left[X_i(s+t) - \overline{X_i} \right] \left[(X_j(s) - \overline{X_j}) \right] \tag{2}$$

where are X_i and X_j are the two different time series, t is a particular observation, T is the whole time series, s is the scale estimator, c is the correlation or covariance of these observed pairs. In this case, autocorrelation is not symmetric in t for $i \neq j$.

In our context, we were seeking the association between time series of fire activity (y) related to past lags in each fire danger index (x). A set of 4 lags (0, 1, 2 and 3 months) was established as the maximum time window of weather influence.

With the purpose of assessing inter-annual dynamics of fire activity and FWI, BI and FFDI, we applied the Mann-Kendall test (MK) coupled with Sen's slope (SS); this combination allows us to identify statistical significant trends and quantify the magnitude of the change. MK is a non-parametric statistical test suitable for identifying trends in times series (Kendall, 1975; Mann, 1945). This test contrasts the null hypothesis (H_0) and alternative hypothesis (H_1) of non-existence or existence of trend, respectively. MK outputs are the $\mathcal{T}$ value, whose value determine the sign of the trend (upward: $\mathcal{T} > 0$; downward $\mathcal{T} < 0$); in turn the significance level of the test identifies significant trends (p-value < 0.05). Then, we evaluated the magnitude of the changes by means of SS (Sen, 1968). SS is also a non-parametric procedure that estimates the median slope by joining all pair-wise combinations of observations.

2.4.3. Local correlation analysis and mapping

To identify spatial patterns in fire-weather associations, we applied correlation analysis at pixel level by means of the Pearson's R correlation coefficient (Best and Roberts, 1975; Hollander and Douglas, 1973). Pearson's R is a parametric statistical test that indicates the extent to which two variables are linearly related. The test requires at least one of the variables to be normally distributed; in our case, the three fire danger indexes (FWI, BI and FFDI) fulfil this requirement. Pearson's R ranges between +1 and −1, where 1 is perfect positive linear correlation, 0 is no linear correlation, and −1 is negative linear correlation. We calculated and mapped Pearson's R at grid level for each fire-activity subset (Fig. 3) reporting the R correlation coefficient and its statistical significance ($p < 0.05$). The process was repeated using each weather index.

3. Results

3.1. Relationships between fire weather danger and fire activity

Fig. 4 and S1-S2 (Appendix) show the temporal evolution of the

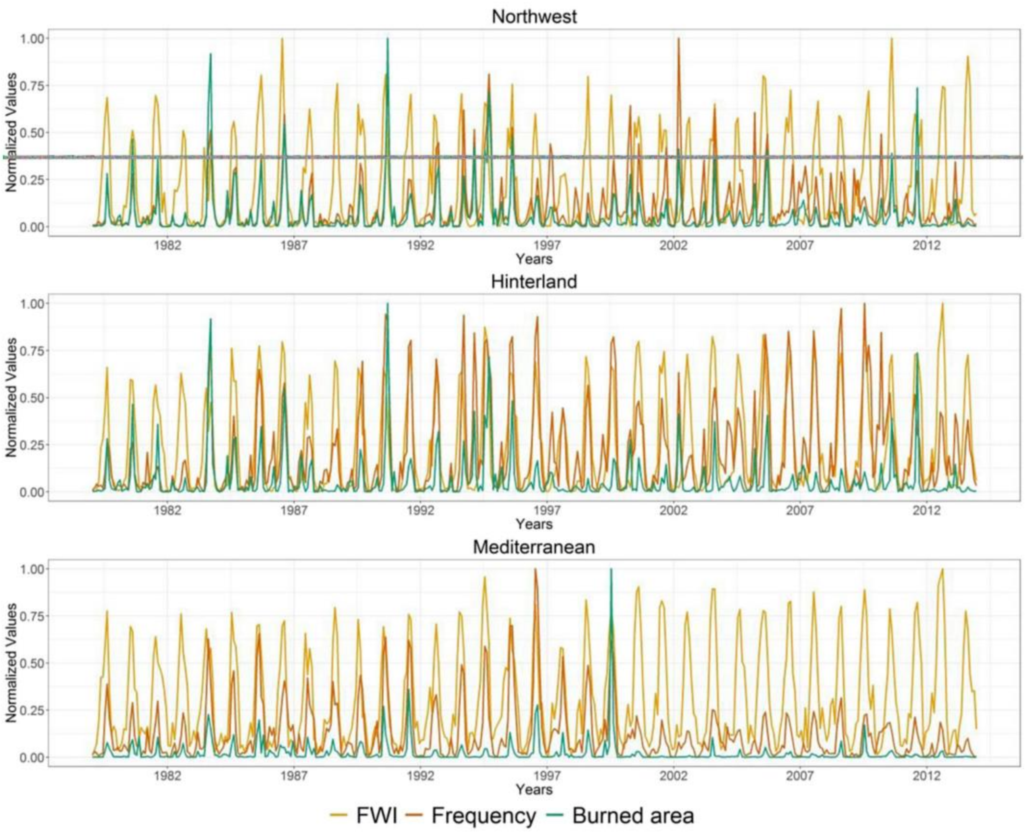

Fig. 4. Time series of FWI (yellow line), fire frequency (red line) and burned area (green line). All variables are normalized into a 0–1 range. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

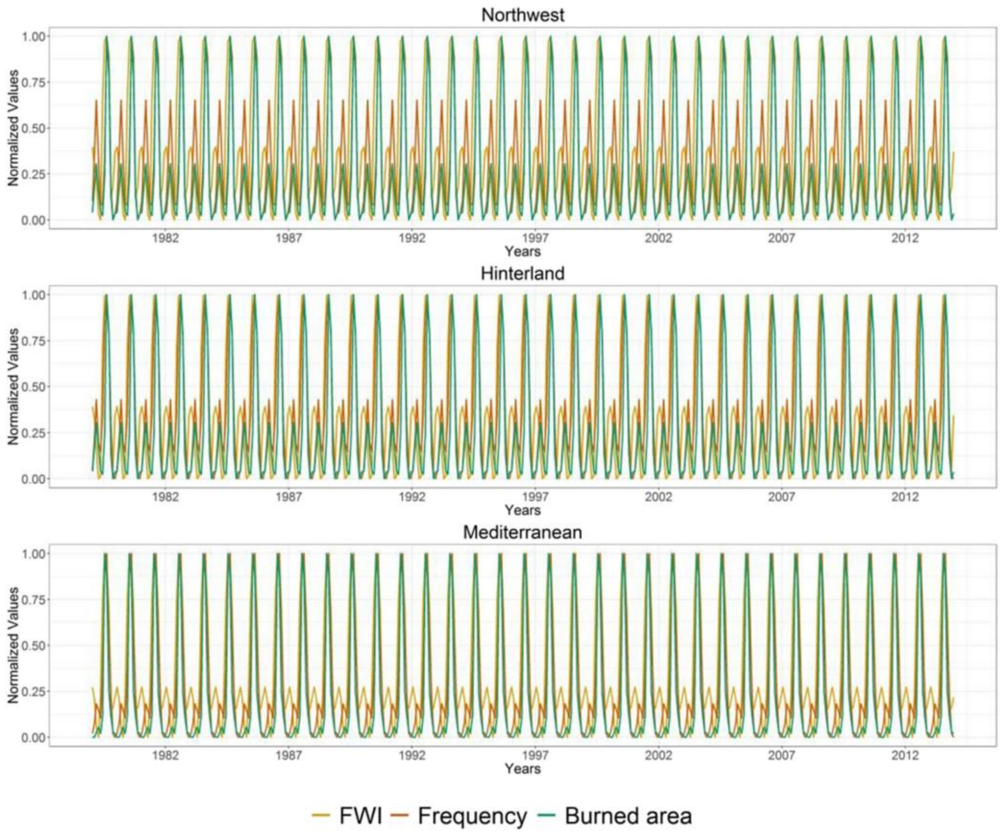

Fig. 5. Time series of seasonal component of FWI (yellow line), fire frequency (red line) and burned area (green line). All variables are normalized into a 0–1 range. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

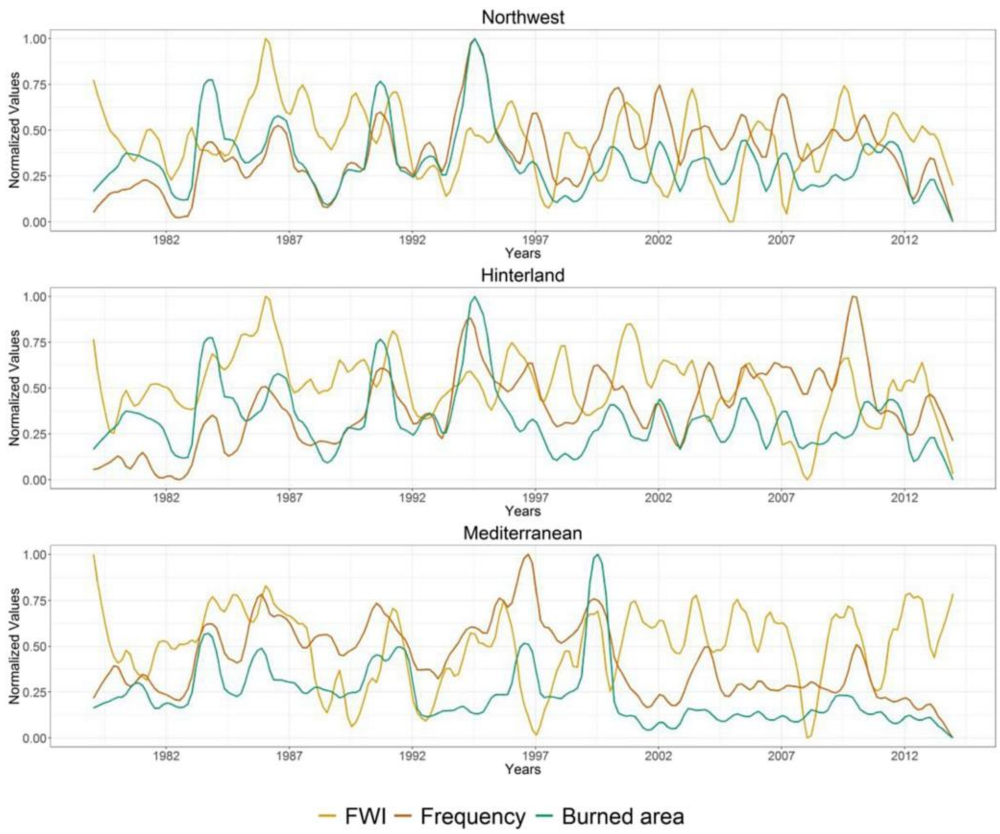

Fig. 6. Time series of trend component of FWI (yellow line), fire frequency (red line) and burned area (green line). All variables are normalized into a 0–1 range. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

Table 2
Cross-correlation coefficients between seasonal plus random effects components of FWI, BI and FFDI by monthly lags (−3, −2, −1 and 0) and fire frequency and burned area by region (NW: Northwest, HL: Hinterland and MED: Mediterranean).Fire features were log-transformed and normalized before the analysis.

Region	Fire feature	FWI				BI				FFDI			
		Lag −3	Lag −2	Lag −1	Lag 0	Lag −3	Lag −2	Lag −1	Lag 0	Lag −3	Lag −2	Lag −1	Lag 0
NW	Frequency	−0.27	**0.10**	**0.36**	**0.38**	−0.29	0.02	**0.33**	**0.40**	−0.27	0.05	**0.32**	**0.41**
	Burned area	−0.25	**0.10**	**0.36**	**0.38**	−0.28	0.01	**0.31**	**0.39**	−0.24	0.06	**0.32**	**0.40**
HL	Frequency	−0.26	**0.20**	**0.55**	**0.64**	−0.28	**0.15**	**0.50**	**0.61**	−0.24	**0.20**	**0.55**	**0.65**
	Burned area	−0.23	**0.11**	**0.36**	**0.35**	−0.26	**0.10**	**0.38**	**0.38**	−0.22	**0.10**	**0.35**	**0.36**
MED	Frequency	−0.15	**0.29**	**0.63**	**0.73**	−0.21	**0.22**	**0.57**	**0.64**	−0.19	**0.24**	**0.62**	**0.75**
	Burned area	−0.08	**0.30**	**0.62**	**0.70**	−0.17	**0.21**	**0.55**	**0.64**	−0.12	**0.26**	**0.61**	**0.72**

Values in bold represent correlations greater than +0.10.

FWI-BI-FFDI (respectively) and fire features at regional level. Generally speaking, the connection between fire danger indices and fire features is noticeable. For instance, fire frequency in the Hinterland and Northwest region closely follows the temporal fluctuation of fire danger whereas the Mediterranean greatly differs since the mid-90s.

The seasonal decomposition of fire activity reveals a secondary peak in late winter-early spring particularly noticeably in the Northwest region for fire frequency (Fig. 5 and S3-S4 Appendix). However, as we move towards the Mediterranean region, the magnitude of this secondary peak decreases. In turn, the trend component of fire danger has been progressively increasing in all regions (Fig. 6 and S5-S6 Appendix). Nonetheless, fire activity shows different tendencies depending on the region. The Northwest region is the most stationary, although during the last decade fire features depict a downward trend. The Hinterland region showed an increase until 2010, decreasing afterwards. In the case of Mediterranean, this decline is also present since 2000.

Results from cross-correlation support and complement the aforementioned seasonal performance. We detect a generalized and strong positive association between seasonal fire activity and fire danger indices (Table 2). Overall, correlations are statistically significant in lags 0 and -1, decreasing and losing significance as lag increases. Correlations in N are usually greater than in BA, and higher in FWI than in BI-FFDI; although regional dissimilarities do exist. The MED region shows the highest correlations for FFDI ($N_{lag=0}$ = 0.75, $N_{lag=-1}$ = 0.62; $BA_{lag=0}$ = 0.72, $BA_{lag=-1}$ = 0.61) followed by HL ($Nl_{=0}$ = 0.65, Nl = −1 = 0.55; $BA_{l=0}$ = 0.36, $Ba_{l=-1}$ = 0.35). The most streaking result from this analyses is the moderate correlation values observed in the NW region for FWI ($N_{l=0}$ = 0.38, $N_{l=-1}$ = 0.36; $BA_{l=0}$ = 0.38, $BA_{l=-1}$ = 0.36). This fits the expected behavior of the region given its secondary occurrence peak in fire incidence during winter related to agricultural burnings.

One of the most remarkable findings is the consistent positive trend of FWI-BI-FFDI across regions, thus mainland Spain experiences increased fire weather potential over time. Nonetheless, fire activity performs differently across regions (Table 3). Fire frequency shows significant and positive trends only in NW and HL, more intense in the NW region (SS 0.49 *vs.* 0.20). On the contrary, fire occurrence in the MED region tends to decay. Burned area displays non-significant trends in all the study regions excluding MED, with a significant negative trend. Hence, it is obvious that the evolution of fire activity differs from the one by FWI-BI-FFDI in most of the study area. This is noticeable in the disconnection of fire danger indices and fire activity in the Mediterranean after the 90s (Fig. 4 and S1-S2 Appendix).

Table 3
Mann-Kendall coefficients Tau and Sen's slope output of trend component of the decomposed time series of FWI, BI and FFDI, fire frequency and burned area in each region. Significant cases (p value < 0.05) are denoted by an asterisk. Only burned area was log-transformed and normalized before analyses.

Fire feature	Northwest		Hinterland		Mediterranean	
	Tau	Sen's slope	Tau	Sen's slope	Tau	Sen's slope
FWI	0.31*	0.001	0.49*	0.001	0.39*	0.001
BI	0.36*	0.001	0.52*	0.001	0.39*	0.001
FFDI	0.40*	0.001	0.58*	0.001	0.46*	0.001*
Frequency	0.24*	0.49*	0.36*	0.20*	−0.28*	−0.13*
Burned area	0.01	0.00	0.02	0.00	−0.39*	−0.01*

Therefore, short-term weather conditions have limited ability to control dynamics in fire activity other than seasonal cycles, at least at global/regional level. In general, fire danger seems to be more related to intra-annual cycles of fire activity while has a limited influence on long-term trends.

3.2. Differences between fire danger indices by fire feature and fire-activity subset

At a first glance, regarding local level, the association of fire activity with weather indices is greater in the seasonal component and, in general, stronger for fire frequency than for burned area. This is inferable from the higher value of the correlation coefficients and the larger number of significant locations we found. Overall, fire danger indexes are better linked to fire ignition source than fire size; however, differences were detected in terms of spatial patterns and also depending on the ignition source or the final area of the fires. Additionally, the remainder component is usually more correlated with human caused fires above 1 ha. In turn, the spatial patterns observed across fire weather danger rating indices resemble one another, depicting a similar picture when comparing either components of time series or fire-activity subsets (Figures from S7 and S8 Appendix). In any case, BI (Figs. 7 and 8) seems to provide more insightful outputs in terms of Pearson's coefficients and spatial patterns, not only in the seasonal component as well as in the trend component. On the other hand, the others fire danger indices (FWI and FFDI) show similar

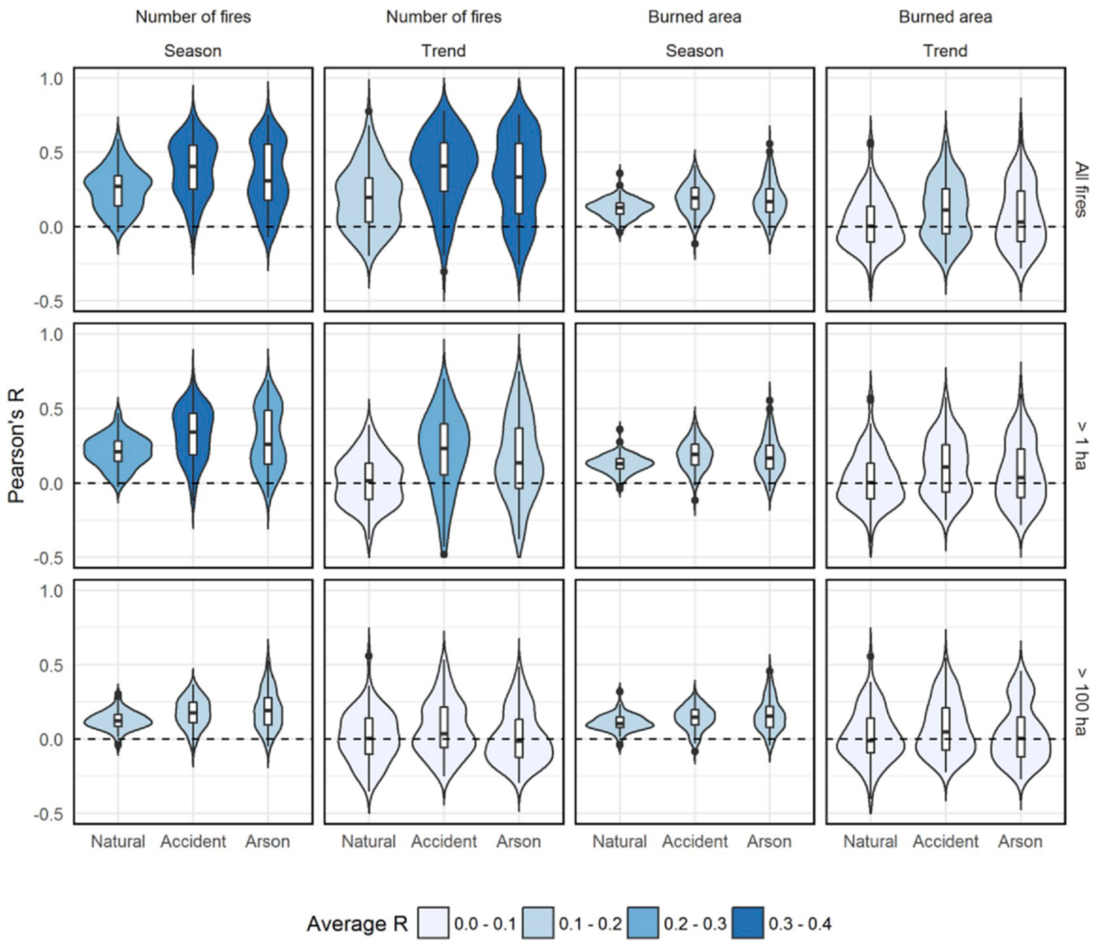

Fig. 7. Statistical distribution of the Pearson's R between total number of fires-burned area and BI. Blue gradient categories show the average of Pearson's R of pixels in each fire size-cause subset and component (season and trend). (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

average Pearson's R (Figs. S9 and S10 Appendix).

At a seasonal level, significant correlations were found in the whole study area regardless of the fire-activity subset or fire feature. However, natural-caused fires portray a more homogenous pattern compared to those triggered by a human-related source. R's values in natural fires are consistently higher and positive, whereas we observe spatial gaps of low (and even negative) correlation values in the central North and East area in the case of anthropogenic fires, especially in arson fires. This pattern is not observed in large fires, which tend to be positively related at seasonal level irrespective to the source of ignition.

The trend component performs differently, displaying contrasting situations across fire-activity subsets. Overall, burned area shows weak association with fire weather indices, even though significant values area detected. In that regard, more than 40% of the significant locations display negative associations, suggesting poor influence of weather over burned area trends. The yearly evolution of natural fires seems to be slightly linked to weather trends in the Northeastern end but only in the case of the number of small fires. Correlation values in the remaining fire-activity subsets of natural fires are, on average, below the 0.46 threshold in the case of fire frequency and 0.17 in burned area. Nonetheless, locations within the Hinterland and Mediterranean regions display significant and positive correlations in the case of frequency of small-to-medium human-caused fires. The effect of size over trend correlations is fairly sturdier than in the seasonal component; correlation values decrease as fire size increases, as is noticeable in both unintended and arson fires.

Finally, the remainder component –which maybe ultimately linked to extreme events or anomalies – shows moderate to low correlation values no matter the subset. However, the most outstanding result is the occasional existence of positive and significant associations in some fire-activity subsets. These are more noticeable and widespread in fire frequency than in burned area. If we focus on all fires or those above 1 ha burned, the association is found significant elsewhere in terms of number of fires. If we only account for large fires, then significant relationships are limited to the Northwest region. This pattern is also observed in the case of burned area, but in this case significant locations are only observed in central and Northwest Spain.

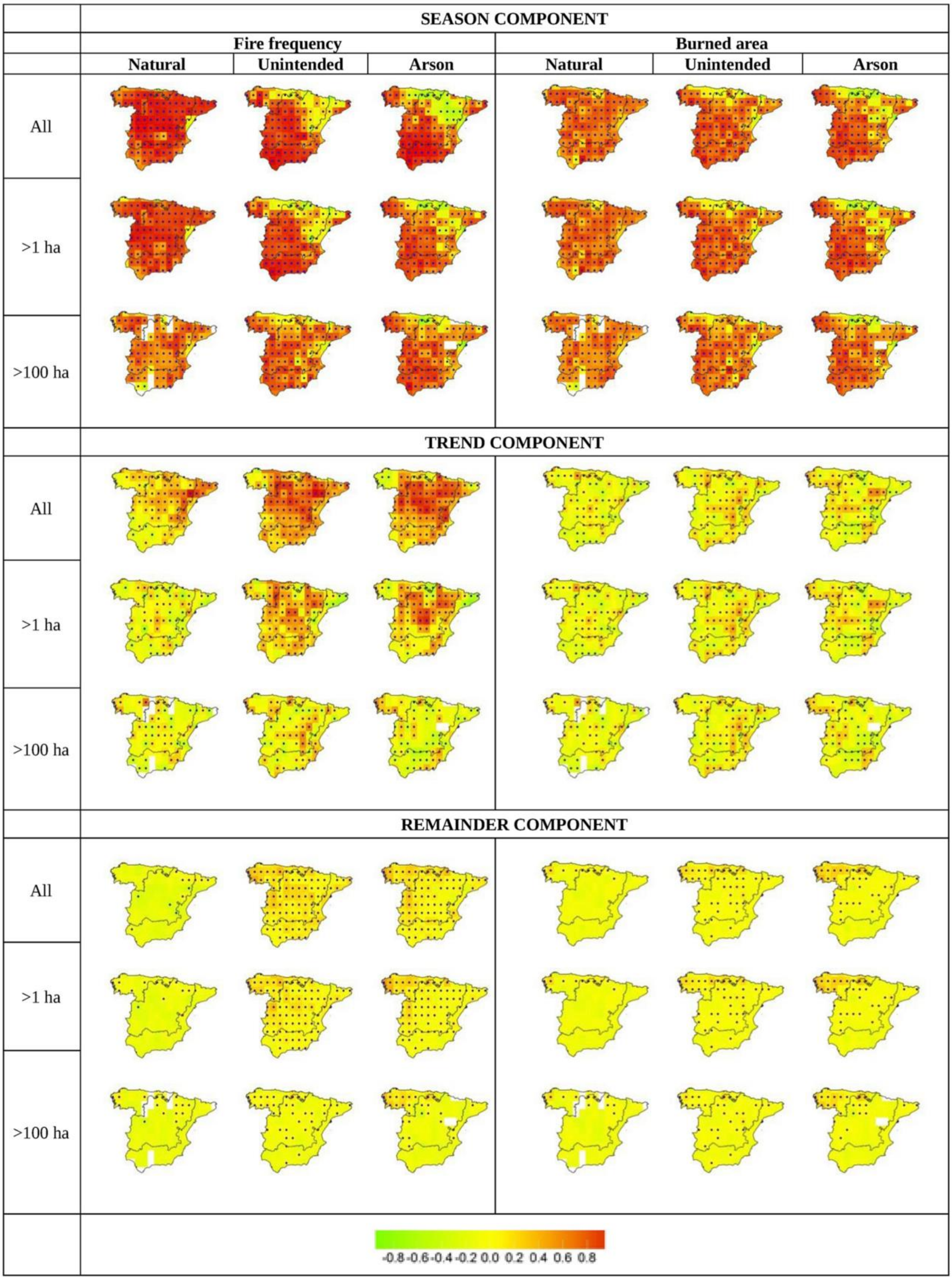

Fig. 8. Spatial pattern of Pearson coefficients between BI *vs*. seasonal, trend and remainder components of fire frequency (left) and burned area (right). Green to yellow values indicate negative association; yellow to red indicate positive association. Points mark significant relationships ($p < 0.05$). Blank pixels indicate no-fire activity in the subset. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

4. Discussion

In this study we explored time-based associations among fire weather danger rating indices and two of the most important fire regime features (i.e. fire frequency and burned area) at regional and local level. This enabled us to understand the diverse contribution of weather conditions to fire incidence by regions, whereas we delve into the detail of the spatial-local distribution of associations depending on fire size and ignition cause.

Our results underline a desynchronize of fire-weather and fire regime in the Mediterranean region since 1994. The reasons that might be explain this aspect is to be linked to a change in firefighting policy such France (Curt and Frejaville, 2018; Fréjaville and Curt, 2015). At the same time, fire danger conditions show a general growth, which has been reported over large forest areas over European Mediterranean countries (Moriondo et al., 2006), due to the rising frequency of years with high fire risk, the longer fire danger season and the greater likelihood of extreme events.

Generally speaking, we observe a close association between short-term (up to 2 months) weather conditions and seasonal cycles of fire activity. The association is stronger in fire frequency than burned area and in the case of BI than in the rest of indexes, although with slight regional differences (Figs. S1 and S2, Appendix). For instance, in the case of fire frequency the correlation is higher in the Hinterland and Mediterranean regions (Jiménez-Ruano et al., 2017b) while the Northwest displays moderate seasonal correlations; likely due to the secondary peak of fire incidence during winter months linked to human activities in the last (Moreno et al., 2014; Sousa et al., 2015). It is worth noting that this region accounts for 75% of arson fires, especially to remove scrub for obtaining pasture for livestock or to reduce stubble (Moreno Rodríguez, 2016). As we expected, CC outputs (Table 2) pointed out that fire weather danger conditions have a remarkable association during the ignition month –lag 0– that weakens towards a month before –lag -1–, although remaining statistically significant.

On the other hand, the temporal evolution expressed as the trend component performs differently. Fire weather indices display significant increasing trends all over the study area (Jolly et al., 2015). In the same line, increased fire occurrence in the Northwest region of mainland Spain (Jiménez-Ruano et al., 2017a) and growing tendency towards severe fire-prone situations in the inland region have already been documented (Martínez et al., 2009; Trigo et al., 2016). Thus, we may conclude that fire frequency tends to increase over time, both in areas where there was already a high incidence and in areas where there was less, so that fire activity becomes spatially more extensive (Moreno Rodríguez, 2016). However, the Mediterranean region seems to behave otherwise, with an overall decrease both in fire ignitions and affected area (Jiménez-Ruano et al., 2017a; Turco et al., 2016). Our findings suggest that, to some extent, trends in fire frequency in the central and north regions are connected with the inter-annual evolution of fire weather indices, except in the case of large fires. On the other hand, the Mediterranean region is somewhat desynchronized from the overall increasing trend of fire weather indices, particularly clear since the 90s (Fig. 4). Furthermore, dynamics in burned area do not appear to be as strongly linked to weather as ignition does. In this sense, it is well-known that fire activity in the Mediterranean region is controlled by longer periods of high temperatures and/or lower fuel moisture (Rivas Soriano et al., 2013). In fact, fire weather conditions represent around 25% of the influence over the spatial distribution of fires in other Mediterranean environments such as the south of France (Ruffault et al., 2017). In contrast, in the south Alps, in the late 20th century the climate influence is decreasing in favor of human activities and fuel availability (Zumbrunnen et al., 2009). According to our findings, this effect is limited to the intra-annual (seasonal) cycles of fire activity but not connected to the inter-annual evolution, i.e., warm and dry periods during summer promote fire incidence but warmer conditions along the years do not favor further fire activity.

The spatial disaggregation of correlation exposed local underlying patterns of association. Again, the link is stronger in seasonal cycles than in temporal evolution, and weaker in burned area compared to fire frequency. Overall, weather conditions influence fire ignition to a higher extent than burned area size. Fire propagation is a more convoluted process involving a number of factors both environmental –fuel load or landscape structure– or anthropogenic –fire suppression (Koutsias et al., 2012; Krebs et al., 2010; Liu et al., 2012; Liu and Wimberly, 2016). On the other hand, accounting for the ignition source or the final size of the fire allows more insightful analyses. In fact, the proportion of small fires has been increasing from the period 1974–1993 and today they remain stable at these high percentages, around 70% (Jiménez-Ruano et al., 2017a; Moreno Rodríguez, 2016). Furthermore, addressing human-related fires separately allowed us to identify spatial gaps of correlation with fire weather indices such as those in fire frequency in the central north area of the country. In this sense, it is well-known that in some locations of the NW, fires are triggered by arsonists taking advantage of dry-warm weather situations (Prestemon et al., 2012), which can ultimately become uncontrolled depending on the fire-fighting capability and availability (Fuentes-Santos et al., 2013).

Seasonal variations in burned area from human-related fires are greatly related to weather conditions, more markedly in the Northwest of mainland Spain. This result is consistent with the work by Trigo et al. (2016), who highlighted the western half of the Iberian Peninsula as more susceptible to large wildfires. Furthermore, unintended fires are also significantly associated to fire weather danger in the north-central and east region. In this sense, Badia et al. (2011) have detected an increase in fire danger in Catalonia explained by mean maximum temperature in July in both scrublands and coniferous forests. In that regard, those indices accounting for fuel moisture (BI and FWI) produce higher correlations and more contrasted spatial patterns than those purely meteorological (FFDI). In contrast, Jiménez-Ruano et al. (2017b) reported a decrease in frequency and burned area for wildfires above 500 ha, likely explained by the improvement in fire suppression investment over the years.

Different local associations were detected in the trend component. The most interesting outcome was found in locations with negative associations between fire weather and fire activity, especially in a number of locations along the Mediterranean coast. Overall, positive associations are expected, i.e., higher fire danger should lead to more fire activity; but the existence of such negative associations suggests that the inter-annual evolution of fire incidence is not fully controlled by weather. This was already observed at regional level in the Mediterranean and also locally in the Northeastern region. However, the HL region brings together some positive correlations with fire weather trends regardless of the cause.

Finally, analyses on the remainder component revealed a certain degree of association between anomalies in fire activity and fire weather indices. This is particularly interesting since these relationships are consistently positive. Thus, there appears to be some connection between random anomalies or extreme events.

However, our work has some shortcomings that should be mentioned. Firstly, the quality of the dataset used in the analysis could be improved in terms of resolution spatial. Secondly, it would be interesting to combine meteorological variables and fire indices to build better models, while improving their predictive power. In this sense, we can find some examples in De Angelis et al. (2015) who have been able to enhance the performance with a Maxent approach. On the other hand, care should be taken with the indiscriminate use of FWI, since in some areas of Italy it has been observed that FWI probably overestimates fire danger, especially during early spring and autumn (Giannakopoulos et al., 2012). Thus, it seems reasonable to move towards a fine tuning of the existing indices, depending on the analyzed environment.

5. Conclusions

In this work we investigate the association between fire danger indices and two of the most common fire regime features, such as number of fires and burned area, in mainland Spain. We have accounted for all fire records in the period 1979–2013 in order to explore the joint influence of FWI, BI and FFDI at regional level, as well as analyzing their own contribution separately at local level.

Our findings suggest that weather conditions control intra-annual (seasonal) cycles of fire activity but have a limited influence on long-term trends. Overall, fire danger is better linked to fire ignition than burned area size, although differences were detected in terms of spatial patterns and also depending on the ignition source or the ultimate size of the fires.

According to cross-correlation outputs, the seasonal influence of weather is stronger during the first two months before the fire, although in some regions such as the Hinterlands it remains statistically significant up to three months. Seasonal burned area correlation outputs seem to be more associated to arson cause in the Northwest, the most fire affected and arson-related region. The assessment of the trend component points towards the independence of fire activity in the Mediterranean losing synchronicity with fire weather danger since 1994. Altogether, it suggests that human factors have taken over weather conditions. In cross-correlations analysis, both FWI and FFDI were considered useful fire indices due to its good performance at regional level while FWI is widely used in the bibliography.

At local level, the comparison of fire weather indices promotes BI as the best suited to analyze fire-weather relationships in the context of mainland Spain due to its higher correlations values. In addition, it seems to work quite well for the seasonal and trend components of burned area.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jenvman.2018.09.107.

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CHAPTER 7: CHANGE IN ANTHROPOGENIC DRIVERS

This chapter describes the results, discussion and main conclusions obtained from the analyses of spatial and temporal evolution of human drivers factors into the fire regime features. We employed various regression models (Logit and Poisson Generalized Linear Models), as well as, trend analysis by means of Mann-Kendall. In addition, Geographically Weighted Regression Models are applied to assess spatial-temporal patterns.

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ORIGINAL PAPER

Analysis of recent spatial–temporal evolution of human driving factors of wildfires in Spain

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Abstract Fire regimes are strongly dependent on human activities. Understanding the relative influence of human factors on wildfire is an important ongoing task especially in human-dominated landscapes such as the Mediterranean, where anthropogenic ignitions greatly surpass natural ignitions and human activities are modifying historical fire regimes. Most human drivers of wildfires have a temporal dimension, far beyond the appearance of change, and it is for this reason that we require an historical/temporal analytical perspective coupled to the spatial dimension. In this paper, we investigate and analyze spatial–temporal changes in the contribution of major human factors influencing forest fire occurrence, using Spanish historical statistical fire data from 1988 to 2012. We hypothesize that the influence of socioeconomic drivers on wildfires has changed over this period. Our method is based on fitting yearly explanatory regression models—testing several scenarios of wildfire data aggregation—using logit and Poisson generalized linear models to determine the significance thresholds of the covariates. We then conduct a trend analysis using the Mann–Kendall test to calculate and analyze possible trends in the explanatory power of human driving factors of wildfires. Finally, Geographically Weighted Regression Models are explored to examine potential spatial–temporal patterns. Our results suggest that some of the explanatory factors of logistic models do vary over time and that new explanatory factors might be considered (such as arson-related variables or climate factors), since some of the traditional ones seem to be losing significance in the presence–absence models, opposite to fire frequency models. In particular, the wildland–agricultural interface and wildland–urban interface appear to be losing explanatory power regarding ignition probability, and protected areas are becoming less significant in fire frequency models. GWR models revealed that this temporal behavior is not stationary neither over space nor time.

Keywords Trends · Wildfire · GLM · GWR · Human driving factors · Occurrence

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1 Introduction

Fire is no longer a significant part of the traditional systems of life; however, it remains strongly tied to human activity (Leone et al. 2009). Knowledge of the causes of forest fires and the main driving factors of ignition is an indispensable step toward effective fire prevention (Ganteaume et al. 2013). It is widely recognized that current fire regimes are changing as a result of environmental and climatic changes (Pausas and Keeley 2009) with increased fire frequency in several areas in the Mediterranean Region of Europe (Rodrigues et al. 2013). In Mediterranean-type ecosystems, several studies have indicated that these changes are mainly driven by fire suppression policies (Minnich 1983), climate (Pausas and Fernández-Muñoz 2012), and human activities (Bal et al. 2011). Human drivers mostly have a temporal dimension, which is why an historical/temporal perspective is often required (Zumbrunnen et al. 2011; Carmona et al. 2012). In Mediterranean Europe, increases in the number of fires have been detected in some countries, including Portugal and Spain (San-Miguel-Ayanz et al. 2012; Rodrigues et al. 2013). In addition, a recent work by Turco et al. (2016) suggests huge spatial and temporal variability in fire frequency trends especially in the case of Spain, where increasing and decreasing trends were detected depending on the analysis period and scale. This increase in wildfire frequency and variability, with its associated risks to the environment and society (Moreno et al. 2011, 2014), calls for better understanding of the processes that control wildfire activity (Bar Massada et al. 2012).

In recent decades, major efforts have been made to determine the influence of climate change on natural hazards, and to develop models and tools to properly characterize and quantify changes in climatic patterns. For instance, Global Circulation Models can provide credible quantitative estimates of future climate change (Randall et al. 2007). In the particular case of wildfire hazard, most climate models are able to derive fire danger components and inputs, and thereby characterize a probable fire regime (Lynch et al. 2007; Chelli et al. 2014). In this regard, a big effort has been invested to explore and assess the influence of climate change on wildfire hazard. For example, several works such as Koutsias et al. (2013) or Harris et al. (2014) revealed long-term positive correlation between fire occurrence and air temperature and heat waves.

However, fire regimes are strongly dependent on human activities (Salis et al. 2013; Archibald et al. 2013). While physical processes involved in ignition and combustion are theoretically simple, understanding the relative influence of human factors in determining wildfire is an ongoing task (Mann et al. 2016). Due to the difficulty of predicting the peculiarities of human behavior, we face a high degree of uncertainty when modeling human-caused forest fires. However, it is clear that human-caused fires that occur repeatedly in a given geographical area are not simply reducible to individual personal factors, and thus subject to pure chance. They are usually the result of a spatial pattern, whose origin is in the interaction of environmental and socioeconomic conditions (Koutsias et al. 2016). This is particularly true in human-dominated landscapes such as Spain, where anthropogenic ignitions surpass natural ignitions, and humans interact to a large degree with the landscape, changing its flammability, and act as fire initiators or suppressors. In such cases, human influence may cause sudden changes in fire frequency, intensity, and burned area size (Pezzatti et al. 2013). A first step is to identify all the factors linked to human activity, establishing their relative importance in space and time (Martínez et al. 2009, 2013). According to Moreno et al. (2014), the number of fires over the past 50 years in Spain has increased, driven by climate and land-use changes. However, this tendency has been recently reversed due to fire prevention and suppression policies. This highlights the influence of changes in the role of human activities as some of the major driving forces. For instance, changes in population density patterns—both rural and urban—and traditional activities have been linked to an increase in intentional fires. In this sense, several works have previously investigated the influence of human driving factors of wildfires in Spain. These works have explored in detail a wide range of human variables (Martínez et al. 2009; Chuvieco et al. 2010) and methods. Specifically, Generalized Linear Models (Vilar del Hoyo et al. 2008; Martínez et al. 2009; Moreno et al. 2014), machine learning methods (Vega-Garcia et al. 1996; Rodrigues and de la Riva 2014), and more spatial-explicit models like Geographically Weighted Regression (Martínez et al. 2013; Rodrigues et al. 2014) have previously been employed. However, all these approaches could be considered as stationary from a temporal point of view, since they are based on 'static' fire data information summarized or aggregated for a given time span. However, the influence of human drivers cannot be expected to be stationary. Zumbrunnen et al. (2012) stress the importance of dealing with the temporal dimension of human drivers of wildfires. Therefore, exploring temporal changes in socioeconomic or anthropogenic drivers of wildfire will enhance our understanding of both current and future patterns of fire ignition, and thus help improve suppression and prevention policies.

The main goal of this paper is answering the following question. Do human drivers of wildfire vary over time and space? To do this, we investigate and analyze spatial–temporal fluctuations in the contribution of the major human factors of forest fire hazard (such as wildland–urban interface, wildland–agricultural interface, tracks, railways, or protected areas) in Spain by fitting GLM and GWR models. We hypothesize that the influence of these socioeconomic drivers on wildfires has changed over this period.

2 Materials and methods

2.1 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. Thus, the total area of the study region was around 498,000 km^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 settlement systems and population structure, productive sector, land-use and land-cover changes, or territory structure. The complexity of the socioeconomic conditions thus plays a determinant role in wildfire assessments, which is especially important when modeling human factors, since this complexity transfers into the relationships between socioeconomic variables and a natural phenomenon such as wildfire, making the assessment less straightforward.

2.2 Method overview

The proposed method aims to address spatial–temporal changes in the contribution of human explanatory factors to wildfires. The method is based on fitting yearly logistic and Poisson GLM (Generalized Linear Models) using historical fire data. These models allow determining the contribution of each covariate analyzing the Z-values of the beta coefficients. These models are fitted using three different temporal scales of aggregation of fire count data—1, 3, and 5 years—in the period 1988–2012, obtained from the EGIF (General Statistics of Wildfires) database. The explanatory variables were constructed using data for different years within the analysis time span in order to reflect possible temporal or ongoing changes (both response and explanatory variables will be introduced and described later). Once models are fitted, trend detection—by means of the Mann–Kendall test—is applied to *Z*-values of beta coefficients, to determine to which extent their contribution varies over time.

Additionally, in order to search for underlying spatial patterns influencing temporal variations, we model the spatial distribution of the explanatory factors using Geographically Weighted Regression (GWR) logit and Poisson models. We fitted separate models for 1990 and 2006 in the 5-year temporal scale, then mapping and comparing the significance ($p < 0.05$) of each explanatory factor in both dates.

All the analysis were developed using the R statistical software (R Core Team 2013), packages *kendall* and *zyp* for trend analysis, and *glm* for model fitting; with the exception of GWR that was conducted using the software GWR v4.0.

2.3 Fire data and response variables

The dependent variable for both GLM and GWR models was built from the Spanish EGIF database using fire records from 1988 to 2012. The EGIF database is one of the oldest wildfire databases in Europe, beginning in 1968 (Vélez 2001). It is compiled by the Spanish Department of Defense Against Forest Fires (ADCIF) in the Ministry of Agriculture, Food, and Environment (MAGRAMA) from forest fire statistical reports. Among other useful information relating to fire events, the reports include the starting point of each fire, recorded on a 10 × 10 km reference grid used by firefighting crews for the approximate location of fire events. Note that this grid is used in this study as the spatial reference data unit, meaning that all data are obtained from or refer to it. Annual human-caused fire count data were retrieved from the EGIF database at grid level, spatializing fire records using the 10 × 10 grid. Figure 1 shows the annual fire occurrence of human-induced fire ignitions from 1988 to 2012.

Two different response variables were constructed from these data for GLM models: Fire counts were used as dependent variable in the Poisson models, and fire count data were also recoded into a binary presence (grid cells with at least 1 fire) or absence (no fire recorded) variable to construct the response variable for the logistic models.

In turn, three different temporal scales or aggregations—1, 3, and 5 years—were explored to account for the effect of fire occurrence temporal (yearly) variability. The response variable used in the Poisson regression models was aggregated as the sum of fire counts using a time moving window procedure, so that data for 3 or 5 years were assigned to the central year of the window. As a consequence, the analysis time spans were reduced accordingly, to 1989–2011 and 1990–2010 for the 3- and 5-year aggregations, respectively. The response variable for the logistic regression model fitting was grouped in a similar way, but in this case as the maximum value instead of the sum. Thus, if at least 1 fire is recorded in one of the years, the grid is classified as fire-present and vice versa.

From these two sets of dependent variables, we are able to investigate driving factors of human-caused wildfires from two different perspectives. On the one hand, count data used in the Poisson models provide insights into factors relating to fire frequency, whereas presence/absence data are used to determine factors explaining fire occurrence regardless of frequency.

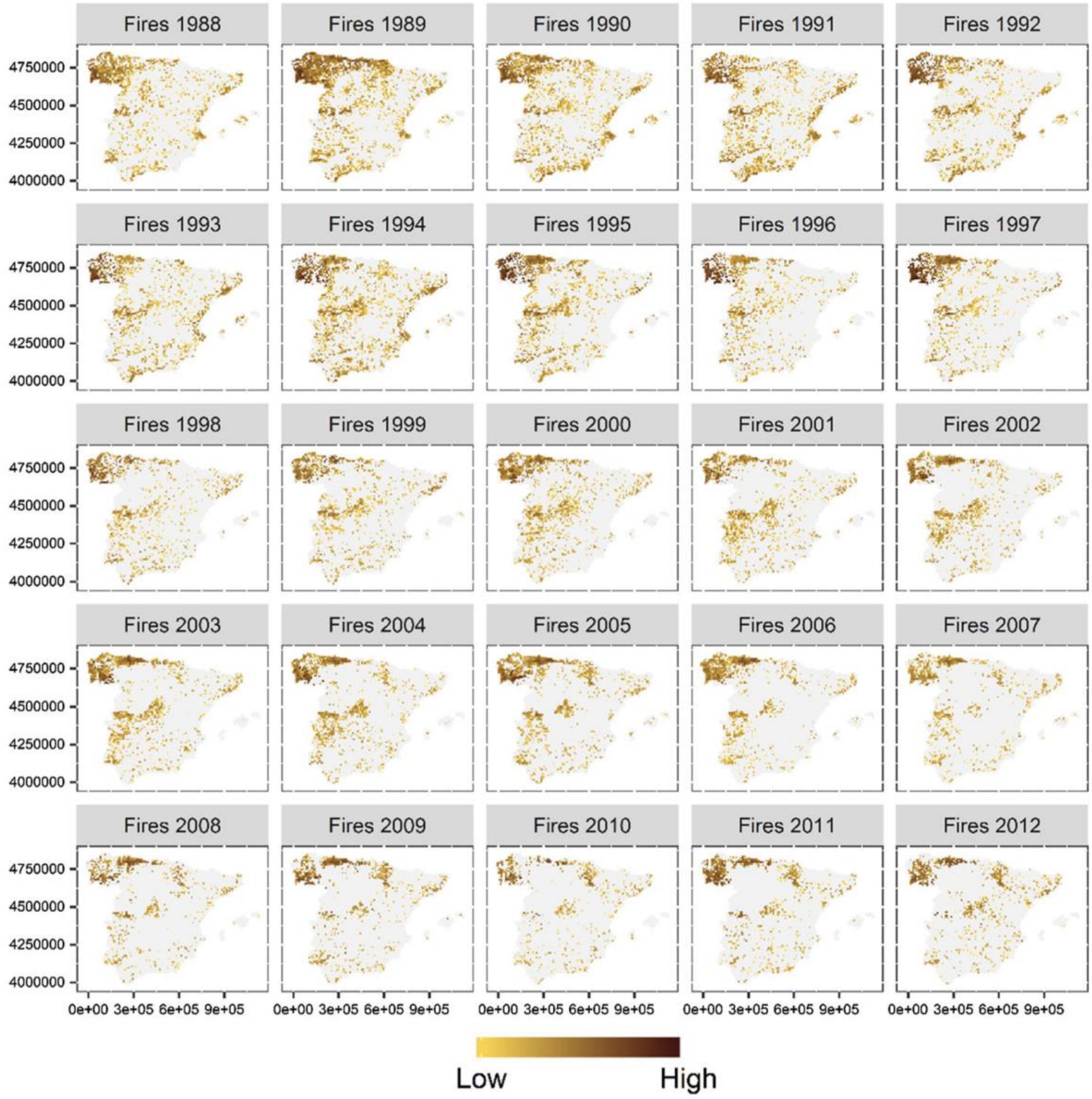

Fig. 1 Spatial distribution of number of human-caused wildfires 1988–2012. Low 0 (*light brown*), high 362 (*dark brown*). No fire displayed in *light gray*

The dependent variable for GWR models was constructed following the same methodology and data. Due to the high computational demand of the GWR method, several assumptions had to be made: (1) only the 5-year temporal scale of fire data aggregation was considered; and (2) only the years 1990 and 2006 were explored. These years were selected based on the reference dates of the Corine land-cover (CLC) project since it is one of the main sources for the explanatory variables.

2.4 Human driving factors

The explanatory variables were selected and spatialized on the basis of the authors' experience with models at regional and national scales (Chuvieco et al. 2010, 2012; Rodrigues et al. 2014; Rodrigues and de la Riva 2014). All these works have explored in detail human drivers of wildfires combining different temporal and spatial scales (national and regional), modeling tools (GLM and GWR), and data (statistical or spatial-explicit information). Specifically, driving factors and explanatory variables were selected on the basis of the studies by Rodrigues and de la Riva (2014) and Rodrigues et al. (2014), in which the main drivers of human causality in mainland Spain were identified. The explanatory variables were classified according to the typology of the affecting factor (Leone et al. 2003) as follows:

1. Factors related to socioeconomic changes

    - Human presence, population increase, and urban growth. Greater pressure on wildlands.
        - *Wildland–Urban Interface* (*WUI*) Length of the boundary between populated and wildland areas inside the 10 × 10 km grid, obtained from CLC for 1990, 2000, and 2006.
        - *Demographic potential* (*DP*) Demographic potential is an aggregate index related to the ultimate potential of the population. It reflects the demographic power of the nation and its ability to provide future population growth. The index was retrieved from Calvo and Pueyo (2008) for 1991, 2001, and 2006 at a spatial resolution of 5 × 5 km, later rescaled (according to the average value) to the 10 × 10 km grid.

2. Factors related to traditional economic activities in rural areas

    - *Agriculture* Use of fire to eliminate harvesting wastes and to clean cropland borders. These procedures are a potential source of ignition due to spread of fire to forest areas in the vicinity
        - *Wildland–Agricultural Interface* (*WAI*) Length of the boundary between agricultural and wildland areas inside the 10 × 10 km grid, obtained from CLC for 1990, 2000, and 2006.

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

    - Electric lines. Possible cause of ignition by accident.
        - *Power lines* (*PWL*) Length of the high-, medium-, and low-voltage transport network inside the 10 × 10 km grid forest area, obtained from the Numerical Cartographic Database 1:200,000 (BCN200). Power lines are spatialized for 1990, 2000, and 2006 using CLC data on forest area extent for each year.
    - Presence of roads, railways, and tracks and their accessibility. Increased human pressure on wildland.
        - *Railways* (*RR*) Length of the railroad network (excluding the high-speed network) inside the 10 × 10 km grid, obtained from BCN200. Like power lines, railroads are spatialized for 1990, 2000, and 2006 using CLC data on forest area extent for each year.
        - *Tracks* (*TRK*) Length of forest tracks and paths inside the 10 × 10 km grid, obtained from BCN200. Tracks are also spatialized for 1990, 2000, and 2006 using CLC data on forest area extent for each year.

4. Factors which could hamper fires

- *Protected areas* Increasing concern about forest protection.
  - *Protected areas* (*PA*) Delimitation of the area occupied by natural protected areas and the Natura 2000 network inside the 10 × 10 km grid. Protected areas are spatialized on a yearly basis using information about date of declaration available for each individual protected site.

All predictive variables were distributed in space using the 10 × 10 km reference grid. All the explanatory variables were constructed using data for 1990, 2000, and 2006 (except *Demographic potential*, which was retrieved for 1991, 2001, and 2006, and protected *areas*, which was constructed separately for each year in the period 1988–2012). In this way, we were able to reflect the change over time of the explanatory factors due to socioeconomic shifts, in case they have occurred. To ensure consistency of results, a collinearity analysis of the explanatory variables was carried out; variables were found to be linearly independent.

2.5 Generalized linear models

GLM are an extension of linear models that can deal with non-normal distributions of the response variable, providing an alternative way to transform the response. The distributions used include those like Poisson, binomial, negative binomial, and gamma. In this study, Poisson and binomial distributions are used to model the relationship of human-induced fires and some of their major driving forces to subsequently explore temporal dynamics in the contribution and significance. These techniques have been traditionally employed in wildfire modeling. Examples of the application of these models to wildfire research can be found in Mann et al. (2016), Martínez et al. (2004a, 2009), Syphard et al. (2008),Vasconcelos et al. (2001), or Zhang et al. (2016). Both regression methods were explored at three temporal scales (1-, 3-, and 5-year aggregation). Table 1 shows the correspondence between the data collection of the independent variables and data collection for the dependent variable, according to the time spans described in Sects. 2.3 and 2.4. Significance thresholds were retrieved yearly from each model subsequently used as inputs in trend detection.

2.6 Trend detection

Temporal trends were calculated using the Mann–Kendall test, a rank nonparametric test (Henry 1945; Kendall 1975), commonly used in environmental research, and suitable for detecting linear or nonlinear trends in data time series (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, respectively, of a trend in the time series of the data. The magnitude of the change was subsequently assessed by means of Sen's slope (1968), a nonparametric alternative for estimating the median slope joining all possible pairs of observations.

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 $i = 1,2,3,\ldots, n - 1$ 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

Table 1 Correspondence between data collection of independent variables and year of data collection for the dependent variable and regression model

1988	1989	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000
WAI90	WAI90	WAI90	WAI90	WAI90	WAI90	WAI90	WAI00	WAI00	WAI00	WAI00	WAI00	WAI00
WUI90	WUI90	WUI90	WUI90	WUI90	WUI90	WUI90	WUI00	WUI00	WUI00	WUI00	WUI00	WUI00
DP91	DP91	DP91	DP91	DP91	DP91	DP91	DP91	DP01	DP01	DP01	DP01	DP01
TRK90	TRK90	TRK90	TRK90	TRK90	TRK90	TRK90	TRK00	TRK00	TRK00	TRK00	TRK00	TRK00
RR90	RR90	RR90	RR90	RR90	RR90	RR90	RR00	RR00	RR00	RR00	RR00	RR00
PWL90	PWL90	PWL90	PWL90	PWL90	PWL90	PWL90	PWL00	PWL00	PWL00	PWL00	PWL00	PWL00
PA88	PA89	PA90	PA91	PA92	PA93	PA94	PA95	PA96	PA97	PA98	PA99	PA00
2001	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**–**
WAI00	WAI00	WAI00	WAI06	WAI06	WAI06	WAI06	WAI06	WAI06	WAI06	WAI06	WAI06	–
WUI00	WUI00	WUI00	WUI06	WUI06	WUI06	WUI06	WUI06	WUI06	WUI06	WUI06	WUI06	–
DP01	DP01	DP01	DP06	DP06	DP06	DP06	DP06	DP06	DP06	DP06	DP06	–
TRK00	TRK00	TRK00	TRK06	TRK06	TRK06	TRK06	TRK06	TRK06	TRK06	TRK06	TRK06	–
RR00	RR00	RR00	RR06	RR06	RR06	RR06	RR06	RR06	RR06	RR06	RR06	–
PWL00	PWL00	PWL00	PWL06	PWL06	PWL06	PWL06	PWL06	PWL06	PWL06	PWL06	PWL06	–
PA01	PA02	PA03	PA04	PA05	PA06	PA07	PA08	PA09	PA10	PA11	PA12	–

than a data value from an earlier time period, the statistic *S* (score) 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).

Both the Mann–Kendall test and Sen's slope were applied to *Z*-values of beta coefficients from yearly logistic and Poisson GLM models at the three proposed temporal scales.

2.7 Model performance and influence of climate factors

Model performance has been investigated in models at the 5-year temporal scale. Performance of logistic models was evaluated using the area under the receiver operation curve (AUC; Hanley and McNeil 1982), whereas Poisson models were assessed in terms of RMSE. This allows determining to which extent we can trust the outcomes of the models as well as investigate the temporal evolution of model performance.

In addition, in order to explore the influence of biophysical factors, we fitted an alternative version of the 5-year logit and Poisson models including climate data (average annual mean temperature and average annual precipitation) from the WorldClim database (Hijmans et al. 2005) version 2. WorldClim is a set of global climate layers (gridded climate data) available at several spatial resolutions, specifically developed for ecological modeling on GIS. Currently, WorldClim provides several datasets for different temporal scenarios (past, current, and future conditions). In this work, we used data for the current conditions scenario (1970–2000).

A comparison of models with (Human-Climate) and without (Human-only) climate factors has been investigated. We analyze AUC and RMSE—for logit and Poisson models, respectively—comparing both scenarios. In this way, we can establish to which extent changes in model performance can be endorsed to climate factors.

2.8 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, k_{th} is the independent variable, and the Gaussian error at location *i*; (u_i, v_i) is the *x*–*y* coordinate of the i_{th} location; and coefficients β (u_i, v_i) are varying conditionals on the location.

Such modeling 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 drawn 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. In addition to the regression coefficients, a GWR model calculates several useful statistical parameters to analyze the spatial behavior of each explanatory variable, such as the value of the Student's t test, which is used to determine the level of significance. On the other hand, GLM approaches such as Geographically Weighted Logistic Regression (GWLR) and Geographically Weighted Poisson Regression (GWPR) have been incorporated to GWR to extend its functionality (Fotheringham et al. 2002; Nakaya et al. 2009). The GWR approach has been already explored in several works such as Koutsias et al. (2010), Martínez et al. (2013) or Rodrigues et al. (2014).

These two methodologies—GWLR and GWPR—are used in this study to complement the results from GLM. Several parameters have been accounted for when calibrating GWR models. Kernel shape and type, bandwidth selection and optimization parameters, or the local or global nature of the predictors (see Nakaya et al. (2009) for further details of both method and software). In this work, GWR model fitting was carried out using Fixed Gaussian Kernel bandwidth, optimized according to the value of AICc, considering all the predictors as local covariates.

3 Results

3.1 Generalized linear models

Results for logistic regression are a proxy for analyzing whether a fire is likely to occur. Figure 2 shows the temporal evolution of the significance level and sign (positive or negative) according to the observed *Z*-values for each temporal scale of analysis. A visual analysis of Fig. 2 reveals some qualitative changes in the contribution of several driving factors, such as WAI, WUI, TRK, and PA, at different temporal scales. Most of the explanatory factors are significant right across the analyzed temporal span at any timescale, except for PA and TRK. PA switches its explanatory sense, whereas TRK losses significance toward the end of the study period. It is noteworthy that regardless of the considered timescale, PA changes its significance sign. However, this is more evident at the 5-year temporal scale being positive until 1995, negative since then until 2007, and mostly non-significant in the ending period. It also worth mention that WAI slightly loses explanatory power over time. For instance, looking at the 3- and 5-year scales, *Z*-values of WAI, which are higher than any other variable—although very close to WUI during early years—shrink to values close to DP's and WUI's. A similar behavior is observed in WUI. In turn, DP gains explanatory performance over time reaching WAI's and WUI's *Z*-values at the end of the analyzed time span.

This behavior is also supported by the results of the trend analysis (Table 2), which identifies significant (p value < 0.05) decreasing trends in TRK, and RR in the 1-year scale. In the 3-year scale, almost every explanatory factor shows a decreasing trend but DP, which shows the opposite and WUI with no significant trend detected. Looking at the 5-year scale, a similar behavior is observed. In this case, WAI shows a significant

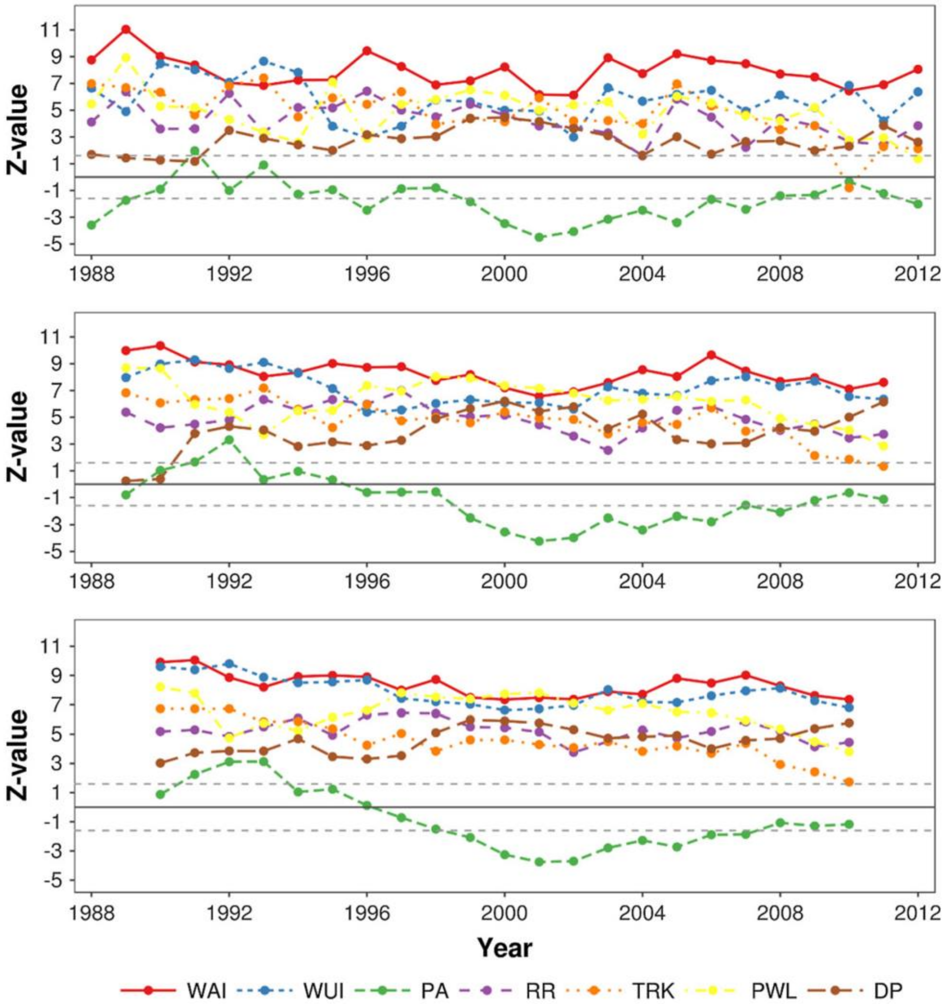

Fig. 2 Temporal evolution of human driving factors. *Z*-values of beta coefficients for logistic regression. *Dashed lines* represent significance thresholds. From *top* to *bottom*, 1-, 3-, and 5-year temporal aggregation scales

Table 2 Results of the trend detection procedure obtained for the logistic regression models at 1-, 3-, and 5-year temporal aggregation scales

	1-year			3-year			5-year		
	τ	p value	Sen	τ	p value	Sen	τ	p value	Sen
WAI	−0.180	0.216	−0.044	**−0.447**	**0.003**	**−0.084**	**−0.381**	**0.017**	**−0.085**
WUI	−0.127	0.388	−0.059	−0.162	0.291	−0.067	**−0.438**	**0.006**	**−0.117**
DP	0.127	0.388	0.028	*0.320*	*0.035*	*0.116*	*0.371*	*0.020*	*0.088*
TRK	**−0.560**	**0.000**	**−0.172**	**−0.668**	**0.000**	**−0.165**	**−0.762**	**0.000**	**−0.201**
RR	**−0.320**	**0.027**	**−0.093**	**−0.320**	**0.035**	**−0.071**	−0.238	0.139	−0.042
PWL	−0.280	0.053	−0.100	**−0.375**	**0.013**	**−0.140**	**−0.333**	**0.037**	**−0.102**
PA	−0.080	0.591	−0.024	**−0.352**	**0.020**	**−0.157**	**−0.362**	**0.024**	**−0.226**

Italics represent decreasing significant trends. Bold represents increasing significant trends

Significance threshold $p < 0.05$

decreasing trend, same as WUI. RR's trend becomes not significant. DP shows an increasing trend at the 5-year temporal scale. According to Sen's slope, the strongest trends were detected for TRK and PA at the 5-year scale, thus being the most variable factors in presence–absence models.

Results obtained for Poisson regression are an indicator of the relationship between fire frequency and the proposed covariates, i.e., the number of fires likely to occur. As in the case of logistic regression models, we can observe changes in the significance and contribution of some of the explanatory factors, such as TRK, RR, PA, and WUI. These changes have been detected both from visual analysis of *Z*-value plots (Fig. 3) and trend detection analysis (Table 3). Same as in the logistic regression models, TRK shows a negative and significant trend (p value < 0.05) at all temporal scales. At the 3-year scale, a significant decreasing trend has been detected in RR. The 5-year scale reveals positive trends in the case of PWL and PA, and a negative trend for WUI. Changes in TRK, RR, and WUI do not imply a loss of significance in their contribution to the models; however, the increasing trend detected in PA leads to a nonsignificant contribution for the latter years of the study period (from 2008 to 2010). PA shows a negative contribution in the first few years, which means that PA zones were related to low fire frequencies; however, the increase in PA *Z*-values leads to a loss of significance since they are slowly approaching zero. Finally, no trend has been identified in the case of WAI regardless of the temporal

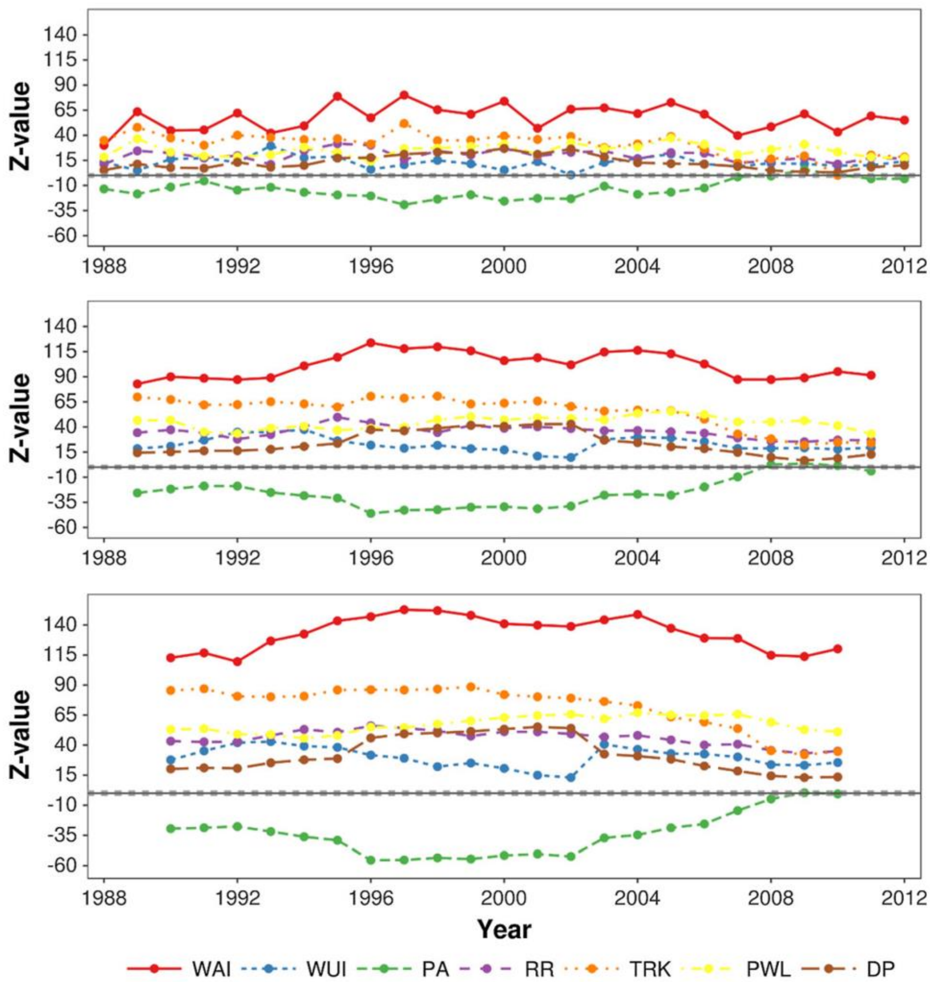

Fig. 3 Temporal evolution of human driving factors. *Z*-values of beta coefficients for Poisson regression. From *top* to *bottom*, 1-, 3-, and 5-year temporal aggregation scales

Table 3 Results of the trend detection procedure obtained for the Poisson regression models at 1-, 3-, and 5-year temporal aggregation scales

	1-year			3-year			5-year		
	τ	*p* value	Sen	τ	*p* value	Sen	τ	*p* value	Sen
WAI	0.027	0.870	0.111	0.020	0.916	0.023	−0.067	0.695	−0.442
WUI	−0.160	0.272	−0.159	−0.225	0.139	−0.305	**−0.324**	**0.043**	**−0.696**
DP	−0.073	0.624	−0.132	−0.067	0.673	−0.192	−0.076	0.651	−0.383
TRK	**−0.480**	**0.001**	**−1.007**	**−0.628**	**0.000**	**−1.957**	**−0.648**	**0.000**	**−2.071**
RR	−0.220	0.129	−0.246	**−0.375**	**0.013**	**−0.549**	**−0.400**	**0.012**	**−0.768**
PWL	0.100	0.498	0.155	0.202	0.187	0.369	*0.390*	*0.014*	*0.804*
PA	0.253	0.080	0.602	0.289	0.057	1.187	*0.343*	*0.032*	*1.390*

Italics represent decreasing significant trends. Bold represents increasing significant trends

scale. This means that this covariate remains stable over time, while keeps being the most important driver of fire frequency.

3.2 GLM performance and influence of climate factors

Figures 4 and 5 show the temporal evolution of model performance in the 5-year logistic and Poisson models, both for Human-only and Human-Climate scenarios. From the visual inspection of these figures, two different behaviors can be identified. Logistic models using only human covariates show a decreasing performance over time, starting from AUC values over 0.7 to values below 0.65. In turn, once we incorporate climate factors (Climate-Human), model performance increases compared to the human-only scenario. What is more, the temporal evolution of AUC, although fluctuates over time, does not decrease as in the case of the human scenario.

On the other hand, Poisson models, even though they show a considerable temporal variation of the RMSE, do not show a contrasting behavior between Human-only and Human-Climate scenarios. In this case, there is almost no difference between the two

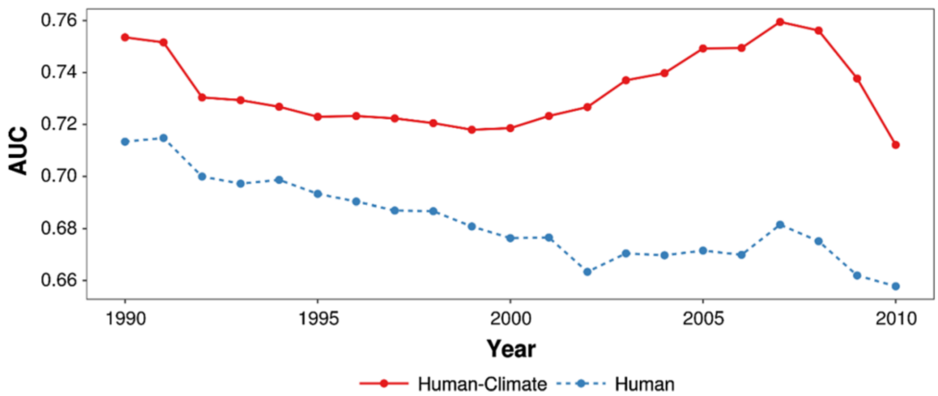

Fig. 4 Temporal evolution of AUC values from human-only and Human-Climate logistic models in the 5-year temporal scale

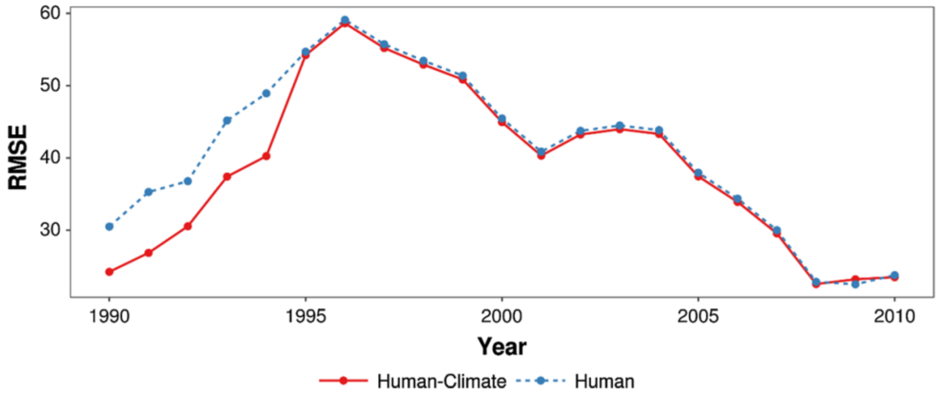

Fig. 5 Temporal evolution of RMSE values from human-only and Human-Climate Poisson models in the 5-year temporal scale

scenarios. This suggests that climate conditions have a less decisive influence in fire counts.

3.3 Geographically Weighted Regression

Global—GLM—models provide insights into the overall behavior of wildfire drivers. To determine whether the detected trends and changes are spatially stationary or not, GWLR and GWPR models have been calibrated at the 5-year temporal scale for 1990 and 2006. As stated before, GWR models have been adjusted using the GWR 4.0 software. It should be noted that this application calculates the significance of the covariates using the Student's t distribution instead of the Z distribution although the interpretation of the results is similar. Tables 4 and 5 summarize the results for GWLR and GWPR models, respectively.

The increase over time of the optimal bandwidth size suggests that there is an underlying spatial change in the contribution of the explanatory factors. This increase, which has been observed in both GWLR (310–880 km) and GWPR (190–450 km) models, implies a reduction in the spatial variability of wildfire drivers.

Table 4 Summary of results for GLM logit and GWLR analysis

Bandwidth (km)	GWLR 1990			GWLR 2006		
	310			880		
t values	Median	Max	Min	Median	Max	Min
WAI	*6.825*	*10.004*	*4.508*	*6.622*	*8.362*	*5.496*
WUI	*7.942*	*9.203*	*3.969*	*5.803*	*5.987*	*5.649*
DP	*1.882*	*2.468*	1.377	1.645	*1.789*	*1.447*
TRK	*5.550*	*8.086*	0.669	*5.536*	*6.735*	*4.757*
RR	*4.027*	*4.750*	*2.377*	*4.820*	*5.149*	*4.416*
PWL	*7.205*	*8.420*	*4.361*	*5.801*	*6.068*	*5.357*
PA	1.040	*3.156*	−1.283	**−1.805**	−1.453	**−2.063**

Significant threshold of *t* values ($p < 0.05$) $\pm$ 1.65. Italics represent negative significant relationship. Bold represents positive significant relationship

Table 5 Summary of results for GLM Poisson and GWPR analysis

Bandwidth (km)	GWPR 1990			GWPR 2006		
	190			450		
t values	Median	Max	Min	Median	Max	Min
WAI	*33.394*	*111.129*	*6.701*	*36.259*	*47.780*	*20.038*
WUI	*26.147*	*59.719*	*11.111*	*9.747*	*13.553*	*6.102*
DP	*12.037*	*99.781*	0.317	*5.254*	*8.529*	*2.228*
TRK	*37.871*	*82.092*	**−6.944**	*16.562*	*17.545*	*11.406*
RR	*18.118*	*27.558*	−0.198	*18.351*	*23.402*	*10.147*
PWL	*24.932*	*42.482*	**−6.173**	*24.418*	*26.269*	*16.027*
PA	**−5.260**	3.799	**−26.150**	**−5.052**	**−3.326**	**−7.360**

Significant threshold of *t* values ($p < 0.05$) $\pm$ 1.65. Italics represent negative significant relationship. Bold represents positive significant relationship

The change in the contribution of each factor follows a pattern similar to the observed in GLM logit models, with WAI, WUI, TRK showing a decrease in their contribution to the probability of occurrence in the 5-year scale. However, the increase in DP's contribution detected in GLM logit is missing in GWLR models. This may occur because in GWR models we compare 1990 and 2006, and the increase in DP's significance strengthens in last years after 2006 (Fig. 2). The decrease in PA is also observed in GWLR models. Same as GLM, PA starts from a positive contribution (the more protected the more affected) to become a deterrent factor in 2006.

Figure 6 shows the spatial distribution of changes from 1990 to 2006 in GWLR (first three columns on the left) and GWPR (last three columns on the right) models. The first two maps are showing the spatial distribution of significance ($p < 0.05$) obtained from the spatial distribution of *t* values in 1990 and 2010. We use a three-color code to represent whether a covariate is significant and positive (red), significant and negative (light green), or nonsignificant (light yellow). A third map summarizes the changes in *t* values from 1990 to 2010. In this way, we can explore whether there is an increase or decrease in *t* values—regardless being significant or not. Therefore, we can determine if and where a given covariate gains or losses contribution to the explanation of wildfire.

As can be seen, almost all covariates in GWLR keep a similar spatial pattern in terms of explanatory sense and significance level ($p < 0.05$). For instance, WAI, WUI, TRK, and PWL are significant and positive all over the study region in both 1990 and 2006. The only factors that present a loss or gain of significance are DP and PA. DP losses significance in the southern area of Spain toward 2006, but is still significant in the main urban areas, i.e., from the central hinterlands—Madrid—and across the Mediterranean coast—Barcelona to Valencia. In turn, PA gains significance as a deterrent factor in all areas except the northeast region. However, if we look at the differences in *t* values between 1990 and 2006 in GWLR (Fig. 6—right), we can observe that, regardless significance has changed or not, several areas within the study region are experiencing an increase or decrease in *t* values. WAI and TRK increase their explanatory performance across the Mediterranean coast, whereas the remaining territory shows the opposite. WUI is generally losing explanatory power except in the northwestern area of Galicia. DP's *t* values are greater in 2006 in the central area (Madrid). RR's explanatory power is increasing all over the region. Finally, PWL' and PA's *t* values are lower in 2006 than in 1990. Nevertheless, whereas this fact

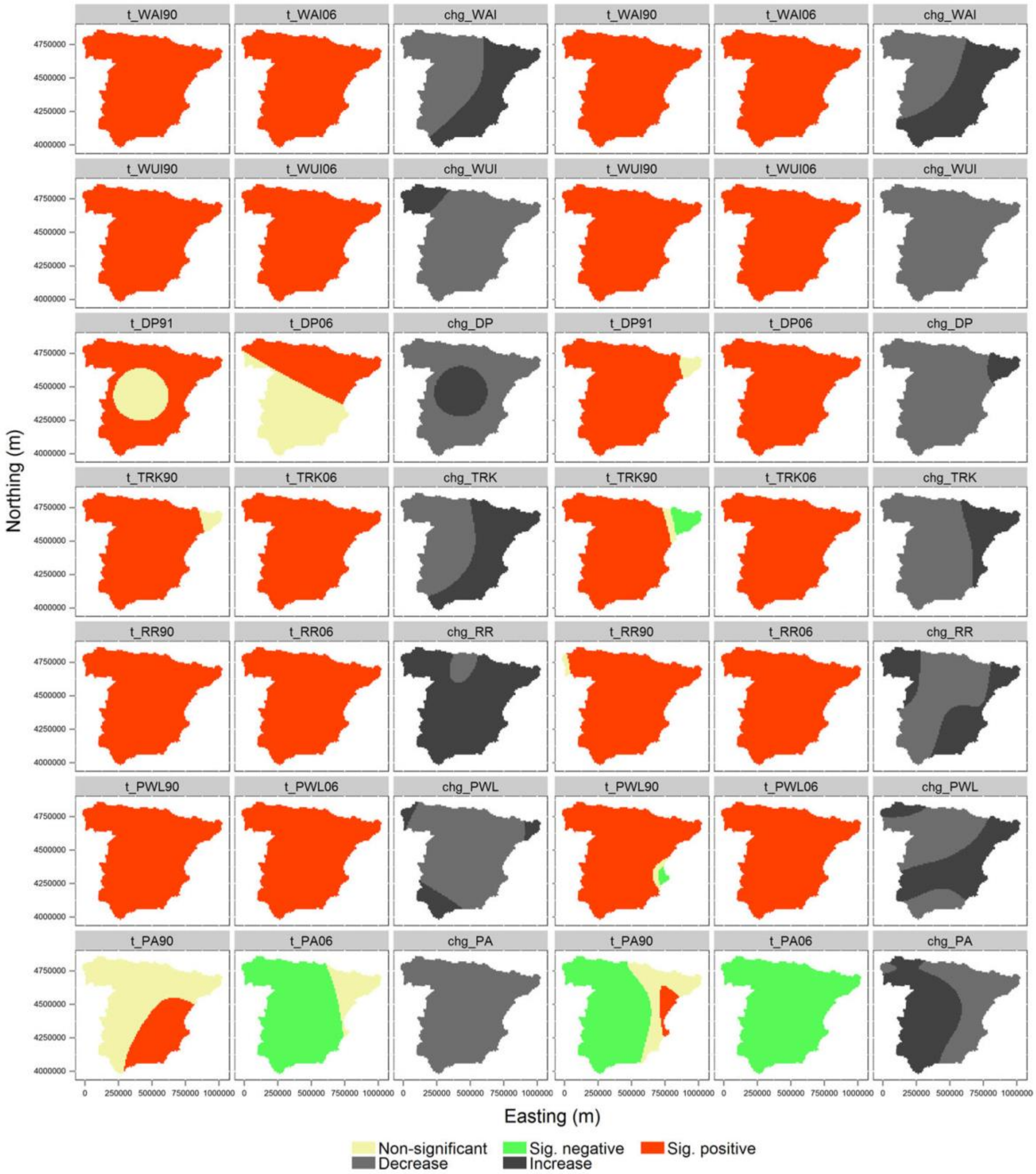

Fig. 6 Spatial distribution of significance of explanatory factors in GWLR (first *three columns* on the *left*) and GWPR (last *three columns* on the *right*) models at the 5-year aggregation scale. Each 3-column map set is organized as follows: *left* 1990; *center* 2006; *right* change 1990–2006

implies a loss of contribution in the case of PWL, it means that PA becomes significant and negative thus preventing fire occurrence.

A similar response has been detected in GWPR (Fig. 6). However, fire frequency drivers show less spatial variation, at least regarding change in significance level. WAI, WUI, and RR are significant and positive all over the region. DP, TRK, and PWL show some small areas that exchange significance but are almost stationary. The greatest change is observed in PA which becomes significant and negative across the study region in 2006, acquiring significance in the eastern area of Spain. Same as GWLR, there are differences in *t* values in GWPR. WAI and TRK present the same spatial pattern that GWLR, increasing *t* values mainly in the Mediterranean coast. WUI losses explanatory performance all over the region. RR and PWL gain explanatory power in both coastal areas. Finally, PA's *t* values decrease in the Mediterranean region, becoming significant and negative as stated previously.

4 Discussion

This paper analyzes the temporal and spatial evolution of several socioeconomic factors relating to human causality of forest fires using historical fire data, GLM and GWR techniques, and trend detection analysis. According to the results, the 5-year scale of fire occurrence aggregation seems the best choice to deal with spatiotemporal changes of fire drivers. This temporal scale allows detecting trends from a statistical standpoint besides 'smoothing' the temporal pattern of evolution so that changes can be visually addressed as well. Logistic regression is used as a proxy to determine the probability of a fire taking place, whereas Poisson models provide insights into the relationship between driving factors and fire frequency. Our results suggest that human driving factors of forest fires have shifted in explanatory power. Both trends in logistic and Poisson models revealed changes in some of the explanatory variables, although more evident in the presence–absence models. Additionally, according to GWR models, the spatial pattern of explanatory performance of driving factors also varies over time in terms of significance and spatial dimension of the models.

GLM logistic regression models suggest a slight loss of significance of traditional explanatory factors, such as WAI and WUI (Fig. 2) supported by findings from GWLR. This is especially important, since agricultural activities have been identified among the most important factors triggering wildfires both in Spain and the European Mediterranean region (Rodrigues et al. 2014; Darques 2015). However, this behavior is not stationary across the study region. The WUI, usually considered the main factor relating to increased fire risk, and traditionally considered the main human ignition factor in the literature (Syphard et al. 2007; Martínez et al. 2009; Romero-Calcerrada et al. 2010; Galiana-Martin et al. 2011), also seems to lose explanatory power, with a significant decreasing trend in the 5-year regression model. However, WUI appears to be replaced by DP, which has increased its explanatory capacity over time according to GLM, although not detected in GWLR. In any case, the interpretation of DP in terms of explanatory sense is similar to WUI's involving increased human pressure on wildlands. However, DP is linked on populated areas close to urban areas, whereas WUI also considers rural settlements closer to forests (Leone et al. 2003). PA has switched its explanatory sense across the analyzed period. PA was related to increased fire occurrence probability during early years, becoming a deterrent factor from the mid-90s until 2007, suggesting increased environmental concern and awareness, but becoming nonsignificant at the end of the time series, although still with negative values.

To this overall variation of explanatory power, we should add that the loss of performance of logistic models in the 5-year temporal scale. The visual analysis of Fig. 4 revealed an increase over time in the contribution of climate factors. The scenario considering only human covariates losses performance possibly because of the loss of explanatory power of WAI and WUI, whereas the Climate-Human models remain more stable and always with higher AUC values. In addition, Climate-Human models are consistently performing better than the human ones.

This behavior can be understood in several ways. First, it could be concluded that the random component of fires associated with human activities is increasing. However, this is unlikely to be the case since human activities are governed by, or at least subject to, socioeconomic patterns (Romero-Calcerrada et al. 2010). On the other hand, it might be that biophysical factors (such as fuel moisture, topography, or climate) are becoming more significant and can thus no longer be excluded, or should be coupled to human factors to determine fire-prone areas when dealing with human-only fire occurrence. Nonetheless, it might be possible that new human explanatory factors are ruling fire occurrence.

According to Fig. 5, the human-only model losses performance possibly because of the loss of explanatory power of WAI and WUI, whereas the Climate-Human model remains more stable. This finding might imply that fire prevention policies are achieving success, since the occurrence of forest fires seems to be less related to human activity and more determined by environmental conditions. In any case, climate and environmental drivers should be explored in greater depth using more accurate data from a temporal point of view, so that yearly climate data are retrieved.

An alternative possibility to explain the observed loss of significance of human driving factors is that maybe other socioeconomic factors are influencing wildfires. These could be accounted for by changes in the socioeconomic models or the establishment of new regulations and/or policies. Despite the increasing contribution of climate factors, AUC values are moderate (Hanley and McNeil 1982), which means there is still a proportion of fire ignition that remains unexplained. In this sense, deliberate fires—which have been increasingly reported since the early 1990s according to the EGIF database (Leone et al. 2009)—remain a source of uncertainty that might explain this. For instance, modeling deliberate fires would contribute to improving the contribution of human factors. The deliberate lighting of a fire or arson can be an action with multiple elements and purposes (Willis 2004) such as revenge or land cleaning. It is thus difficult to synthesize it in terms of explanatory variables, although there have been several proposals in the case of Spain (Martínez et al. 2004b). Variables related to arson have been found to be nonsignificant in structural or historical models (Chuvieco et al. 2010). However, perhaps they should be accounted for—or at least investigated—in this temporal context, given the observed temporal dynamics in some driving factors.

Temporal changes in human factors were also detected in the fire frequency regression analysis. However, in this case, the temporal behavior was rather different. Poisson models do not show strong changes neither in model performance nor in the main drivers of wildfire. Opposite to logistic models, human drivers play a decisive role, whereas climate factors do not contribute to the explanation of overall fire frequency. The WAI remains the most important variable associated with the number of ignitions both in GLM and GWPR models, whereas PA seems to be losing significance, being a deterrent factor at the beginning of the analyzed period and becoming nonsignificant toward 2012. Therefore, considering the results from the logistic and Poisson models in the same picture, it seems that fire occurrence is becoming less dependent on human activities, while fire frequency is still strongly associated with agricultural activities (either by accident or negligence).

In the case of occurrence probability (logistic models), it seems quite clear that human driving factors are evolving over time. Socioeconomic changes during the last decades have driven changes in the structure of the Spanish rural landscape, increasing the complexity of the spatial distribution of the WAI and, accordingly, increasing wildfire probability (Ortega et al. 2012). Trends in fire regimes associated with socioeconomic factors have been identified in previous studies (Rodrigues et al. 2013; Pezzatti et al. 2013; Moreno et al. 2014), supporting our findings. In addition, in recent decades the European and Spanish authorities and governments have proposed and developed several initiatives and legislative procedures aiming to improve fire monitoring and prevention. Among other goals, fire suppression activities or environmental concern and awareness have been strongly supported. Some examples can be found in the *Plan of Priority Action Against Forest Fires* from 1988 (MAPA 1988a), encouraging monitoring and prevention activities by autonomous communities, as well as improvements to infrastructure; the royal decree for the regulation of compensation for the cost of fire suppression (MAPA 1988b), also in 1988; and the European regulations of 1992 (CEE 1992) and 1986 (CEE 1986) promoting prevention through sylviculture, and research into causes, awareness, and professional training. These policies could contribute to the explanation of the changes in human-caused driving factors. In this particular sense, fire prevention activities have been increasingly supported and funded during the last decade. Several initiatives such as the creation of teams for forest fire prevention, awareness campaigns, or promoting the use of forest biomass (MAGRAMA 2012) have been promoted ever since 2002 as a part of the Spanish Forestry Plan along with the Spanish Forest Strategy and the Forest Law.

Finally, GWR models revealed a certain degree of spatial variability. Again, changes are more important in the case of logistic models (GWLR) compared to Poisson ones (GWPR). This is not surprising, since it is well known that the explanatory factors of wildfires in Spain vary over space (Martínez et al. 2013; Rodrigues et al. 2014). Anyhow, spatial changes have been observed in both cases, being particularly interesting the loss of influence of WUI both in GWLR and GWPR. Similar to the global models (GLM), changes in the contribution of PA have been identified in GWLR. Besides the detected change in the spatial pattern of significance according to *t* values, models appear to become local in recent years. The analysis of bandwidth size reveals an increase in the influence area in GWR models. This means that both GWLR and GWPR become 'more global' over time.

5 Conclusions and further work

In this paper, we investigate and analyze spatial–temporal changes in the significance and contribution of the major human factors of forest fire hazards using Spanish historical statistical data records from 1988 to 2012. Our results suggest that the human driving factors of wildfires have undergone significant shifts in their explanatory power in the case of occurrence probability, thus varying over time. However, according to Poisson models, no significant changes have been observed. Consequently, fire frequency is still strongly associated with human drivers and with agricultural activities in particular (WAI).

Nonetheless, logistic regression models revealed a slight loss of significance of traditional explanatory factors. This was especially relevant in the case of the WAI, a variable that has traditionally been linked to forest fire occurrence in Spain, and the WUI, which is the most common driver in the literature. On the other hand, the influence of population density and accessibility (DP) appears to be increasing, so urban pressure on wildlands is a more influencing driver nowadays. Human factors still play a decisive role in fire occurrence, but their overall performance seems to be decreasing over time. In addition, the overall loss of explanatory power of most of the driving factors indicates that biophysical factors (such as fuel moisture, topography, or climate) could be playing a more significant role today. Thus, they can no longer be excluded, but should be coupled to human factors to determine fire-prone areas or in conducting any kind of wildfire assessment. According to our results, fire occurrence is becoming less dependent on human activities, whereas fire frequency remains associated with agricultural activities (by either accident or negligence).

Our findings also open several new lines for future research. The analysis of the GWR models suggests a certain degree of spatial variability, which could imply that human driving factors vary both over space and time. Moreover, deeper insights into the temporal behavior of driving factors can be explored. Specifically, intra-annual—seasonal—variability might be investigated by splitting fire occurrence into summer and winter samples. Finally, the influence of fire size can also be included, isolating large fires so that fire-triggering factors are analyzed separately. This is particularly interesting since most human-induced fires are smaller than 1 hectare. Driving factors might thus vary with fire size.

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Research article

A comprehensive spatial-temporal analysis of driving factors of human-caused wildfires in Spain using Geographically Weighted Logistic Regression

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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. The key objectives of this study are to investigate and analyze spatial-temporal changes in the contribution of wildfire drivers in Spain, and provide deeper insights into the influence of fire features: cause, season and size. We explored several subsets of fire occurrence combining cause (negligence/accident and arson), season (summer-spring and winter-fall) and size (< 1 Ha, 1–100 Ha and > 100 Ha). The analysis is carried out fitting Geographically Weighted Logistic Regression models in two separate time periods (1988–1992, soon after Spain joined the European Union; and 2006–2010, after several decades of forest management). Our results suggest that human factors are losing performance with climate factors taking over, which may be ultimately related to the success in recent prevention policies. In addition, we found strong differences in the performance of occurrence models across subsets, thus models based on long-term historical fire records might led to misleading conclusions. Overall, fire management should move towards differential prevention measurements and recommendations due to the observed variability in drivers' behavior over time and space, paying special attention to winter fires.

1. Introduction

Nowadays it is widely agreed that forest fires are a global threat to ecosystems and landscapes (Pausas and Keeley, 2009) affecting 30–46 million km^2 per year (Randerson et al., 2012). Wildfire has been traditionally known as a natural process responsible for the evolution of forest communities (Pyne, 2009; Wagtendonk, 2009) controlled by multiple factors such as climate, fuel and physiography. Nonetheless, fire remains significantly tied to human activity (Leone et al., 2009) often finding humans acting as both initiators and suppressors, thus altering the natural fire regime (Chuvieco et al., 2008; San-Miguel-Ayanz et al., 2013). This may lead to undesired effects on vegetation structure and composition, the modification of soil properties, increased carbon emissions or hindering ecosystem's services (Doerr and Santín, 2016; Román et al., 2013; Vallejo et al., 2009; van der Werf et al., 2010). In this context, Mediterranean Europe outstands as one of the most fire-affected regions globally while being a highly populated territory with ongoing socio-economic changes influencing wildfire activity (Ganteaume et al., 2013; Vilar et al., 2016). In Mediterranean-type fire-prone ecosystems, such as Spain, several works have reported changes in fire regime (Jiménez-Ruano et al., 2017a) as a result of fire management policies (Moreno et al., 2014), climate (McBean and Ajibade, 2009; Pausas and Fernández-Muñoz, 2012) or human activities (Bal et al., 2011; Vilar et al., 2016).

In recent decades, prevention measures in Spain have gained increased attention after achieving and adequate efficacy in fire suppression (MAPAMA, 2012). In this sense, several initiatives and legislative procedures relating wildfire management have been promoted. We find examples of those policy implementations in the "*Plan of Priority Action Against Forest Fires"* (MAPA, 1988a) or the "*Royal Decree for the regulation of compensation for the cost of fire suppression"* both targeting improvements to suppression infrastructures and also supporting fire monitoring and prevention. Furthermore, fire prevention has been progressively encouraged over the last two decades via National and European regulations (CEE, 1992, 1986; MAPA, 1988b) promoting awareness campaigns, energy production from forest biomass or funding forest fire prevention teams. All these policies and initiatives have most likely induced changes in the drivers of wildfires

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(Moreno et al., 2014).

Up to date, models of human-caused ignition and/or occurrence probability have usually been developed on a long-term basis; regardless of the time cycles that drive human behavior and environmental conditions. Structural models and assessments based on long-term historical fire records have fulfilled a key role discovering and unraveling the function of the main drivers of wildfires. Fire science is now a mature discipline, after having acquired a considerable base of knowledge on either what tools and techniques should we employ (Costafreda-Aumedes et al., 2017); and what factors, variables or drivers must be accounted for (Leone et al., 2003, 2009; Rodrigues and de la Riva, 2014a).

However, human drivers are known to be non-stationary, thus a temporal approach is highly recommended (Carmona et al., 2012; Zumbrunnen et al., 2011). Most attempts to produce fire risk or danger models that actually deal with the human component of ignition are based on long-term historical fire records and stationary predictors (Arndt et al., 2013; Chuvieco et al., 2012; Guo et al., 2016; Martínez et al., 2009; Miranda et al., 2012; Narayanaraj and Wimberly, 2011; Rodrigues et al., 2014; Rodrigues and de la Riva, 2014b). According to Rodrigues et al. (2016), human drivers of wildfire evolved over time, reporting significant shifts in the contribution of anthropogenic factors triggering fires which could, ultimately, be related to recent efforts to improve prevention measures (MAPAMA, 2012) or increased environmental sensitivity to the harmful effects of fire. Knowledge on the causes and drivers of fires is indispensable to achieve effective fire prevention and modeling (Ganteaume et al., 2013). In that regard, the analysis of intra-annual –seasonal– variability of causes, or the influence of fire size on the contribution of human factors is particularly interesting (Jiménez-Ruano et al., 2017b; Pereira et al., 2011; Rodrigues et al., 2014). In this sense, Geographically Weighted Regression is a powerful modeling tool able to capture non-stationary relationships amongst response and predictors. It has been extensively used in several topics (Cardozo et al., 2012; Chalkias et al., 2013; Wang et al., 2013; Xiao et al., 2013) and specifically in wildfire science. Without being exhaustive we found some recent examples of application around the globe (Avila-Flores et al., 2010; Nunes, 2012; Oliveira et al., 2014; Song et al., 2017; William et al., 2017) and in the particular case of Spain (Koutsias et al., 2010; Martínez et al., 2013; Rodrigues et al., 2014, 2016).

In this work we investigate the effect of seasonality, fire size and cause in the explanatory performance of human factors in Spain by means of Geographically Weighted Logistic Regression models (GWLR). To our knowledge this is the first attempt to provide spatial and temporal insights on fire drivers exploring at the same time inter and intra-annual variability coupled to ignition source and resultant fire size, and exploring the Standardized Precipitation-Evapotranspiration index as an ignition driver. Our main goals are to (i) identify spatial-temporal differences in human drivers of wildfires in Spain; (ii) explore dissimilarities in the triggering factors among cause (unintended *vs* arson) and fire size; and (iii) determine whether climate factors are taking over human drivers.

2. Materials and methods

2.1. Study area

The study area is mainland Spain; covering an overall surface around 498,000 km^2. Mainland Spain is a very diverse territory, presenting contrasting topographic, climatic, and environmental (Fig. 1). The relief is characterized by mountain ranges. There are different climatic situations from Oceanic humid conditions (*Cf*) in the northwest areas to Mediterranean and steppe in central, south and east regions (*Cs* and *Bs*). These variety of climates translates into contrasting biogeographical conditions ranging from evergreen coniferous forest (*Pinus radiata* and *Eucalyptus globulus*) in mountain ranges to oak (*Quercus ilex*, *Quercus suber, Quercus robur, Fraxinus excelsior* and *Fagus sylvatica*) and pine forest (*Pinus halepensis*, *Pinus sylvestris*, *Pinus nigra*, *Pinus pinea* or *pinaster*) or scrublands on the Mediterranean. This diversity influences socioeconomic conditions as well. Overall, we find huge differences in the spatial pattern of settlements and population density which peaks mainly along the Mediterranean coast and the central region of Madrid. In turn, complex mosaics of land use and land cover are present all over the regions, ultimately leading to contact areas (the so-called interfaces) between human and forest covers. Therefore, the complexity of socioeconomic conditions plays a decisive role in forest fire assessments (Rodrigues et al., 2014).

2.2. Fire data and response variables

Fire information was retrieved from the Spanish EGIF database (MAPAMA, n.d.). EGIF is the official database on wildfires in Spain, compiled by the "*Departamento de Defensa contra los Fuegos Forestales*" in the Ministry of Agriculture, Food, and Environment from forest fire reports starting in 1968. The EGIF database is one of the oldest and most complete databases in Europe (Vélez, 2001) being built from individual fire reports provided by firefighting services.

For each fire event within the periods 1988–1992 and 2006–2010 we retrieved information about the starting location (recorded on a 10 × 10 km reference grid), ignition source (negligence/accident or arson), fire size, and ignition date. Fires are then split according to their combination of time period ignition source, season (spring-summer, May to September; and fall-winter, October to April) and fire size interval (less than 1 Ha, 1–100 Ha and more than 100 Ha), leading to a total of 24 occurrence subsets. Table 1 summarizes fire count data and Fig. 2 displays the spatial distribution of fire occurrence. Negligence and accidental fires will be further referred to as 'unintended'. Then, we build a set of binary (1-presence and 0-absence) dependent variables for each subset. Each cell where at least one fire has occur was classified as presence and remaining cells as potential absence (Rodrigues et al., 2016).

2.3. Wildfire driving factors

2.3.1. Human driving factors

We selected and constructed human-related covariates according to previous works (Chuvieco et al., 2012; Marcos Rodrigues et al., 2016; Rodrigues et al., 2014; Rodrigues and De la Riva, 2014a), other studies at regional or national scales (Nunes, 2012; Nunes et al., 2016; Padilla and Vega-García, 2011) and a recent review on fire occurrence modeling by (Costafreda-Aumedes et al., 2017). Selected covariates are well-known indicators of fire occurrence and relate to the typology of factors and drivers proposed and described in Leone et al. (2009, 2003):

- *Wildland-Agricultural Interface (WAI)*. Distance of the boundary between agricultural plots (either rainfed or irrigated) and wildlands per grid cell, obtained from Corine Land Cover (CLC) 1990 and 2006.
- *Wildland-Urban Interface (WUI)*. Length of the contact line between urban (populated) and wildland areas within each 10 × 10 km grid, obtained from CLC 1990 and 2006.
- *Demographic potential (DPT)*. The demographic potential is an index reflecting current demographic power as well as the ability to provide population growth in the future. Data on DPT was retrieved from Calvo and Pueyo (2008). It was originally calculated at 5 × 5km resolution and resampled to 10 × 10 km according to the average value.
- *Power lines (PWL)*. Length of electric transport power lines crossing wildland areas within each cell. Network location was obtained from *Base Cartográfica Nacional 1:200,000* (BCN200). Same as WUI and WAI, wildland areas were defined according to CLC 1990/2006.
- *Railroads (RR)*. Length of the conventional railroad network

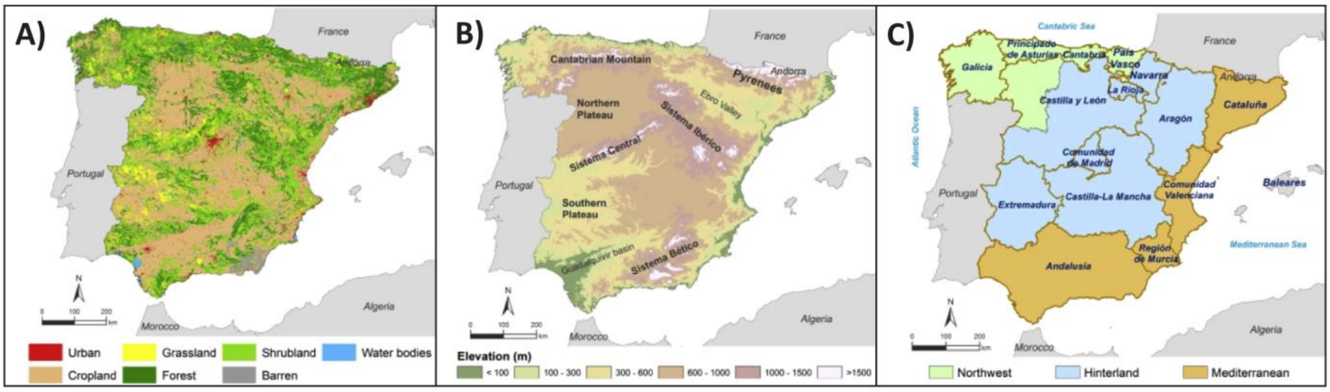

Fig. 1. Study area. A) Land use/cover from Corine Land Cover 2000; B) Relief; C) Administrative division.

Table 1
Total of fire occurrences per period, season, ignition source, and fire size. First parentheses show percentage within the period; second parentheses shows percentage within season.

	1988–1992		2006–2010	
	Unintended	Arson	Unintended	Arson
Spring-summer				
< 1 Ha	3854 (9.5) (15.5)	6376 (15.7) (25.7)	8319 (14) (26.8)	13351 (22.5) (43)
1-100 Ha	2927 (7.2) (11.8)	10859 (26.7) (43.8)	2768 (4.7) (8.9)	6367 (10.7) (20.5)
> 100 Ha	149 (0.4) (0.6)	644 (1.6) (2.6)	104 (0.2) (0.3)	161 (0.3) (0.5)
	6930 (17.0) (27.9)	**17879 (44) (72.1)**	**11191 (18.9) (36)**	**19879 (33.6) (64)**
Fall-winter				
< 1 Ha	1314 (3.2) (8.3)	3234 (8) (20.4)	5366 (9.1) (19)	9994 (16.9) (35.5)
1-100 Ha	1992 (4.9) (12.6)	8991 (22.1) (56.7)	2689 (4.5) (9.5)	9796 (16.5) (34.8)
> 100 Ha	73 (0.2) (0.5)	263 (0.6) (1.7)	36 (0.1) (0.1)	288 (0.5) (1)
	3379 (8.3) (21.3)	**12488 (30.7) (78.7)**	**8091 (13.7) (28.7)**	**20078 (33.9) (71.3)**
TOTAL	10309	30367	19282	39957

crossing wildland areas within each 10 × 10 km grid, obtained from BCN200. Wildland areas were defined according to CLC.

- *Forest tracks (TRK).* Distance of tracks, paths or trails inside forest areas per grid cell (BCN200).
- *Natural protected areas (NPA).* Total area under protected management and belonging to the Natura 2000 network or National Parks.

2.3.2. Climate-related driving factors – Standardized Precipitation-Evapotranspiration index (SPEI)

To explore the potential influence of climate on fire occurrence we computed the Standardized Precipitation-Evapotranspiration index (SPEI); a meteorological drought index that standardize drought across regions endorsed as a key drought indicator (WWO, 2012). Standardized Precipitation-Evapotranspiration was initially proposed by Vicente-Serrano et al. (2009) and later updated in Beguería et al. (2014) and has been employed in recent wildfire analyses such as Turco et al. (2017). The concurrency of high temperatures and extended drought periods boost wildfire activity by promoting larger fires. Several studies report this behavior in southern Europe (Camiá and Amatulli, 2009; Urbieta et al., 2015), the Iberian Peninsula (Trigo et al., 2016) or the Mediterranean sector in Portugal (Ferreira-Leite et al., 2017) or Spain (Piñol et al., 1998; Turco et al., 2013). In our particular case, Rodrigues et al. (2016) suggest an increased role of climate variables (temperature and precipitation) in fire occurrence models. In the present work, SPEI was employed to determine the extent to which this is true, far beyond the already known contribution to burnt area (Turco et al., 2017). Note that SPEI reflects not only climate patterns but also topographic gradients as physiography has a direct influence in the spatial distribution of weather and climate (Martín-Vide and Olcina, 2001).

Standardized Precipitation-Evapotranspiration was computed from climatic data from MOTEDAS (Monthly Temperature Dataset of Spain, Gonzalez-Hidalgo et al., 2015; Peña-Angulo et al., 2016) and MOPREDAS (Monthly Precipitation Dataset of Spain. González-Hidalgo et al., 2011) datasets (1950–2010). Two separate SPEI were calculated, one in 1998-1992 and another for 2006–2010. Both indexes were calculated using a 60 month time window and the Hargreaves equation (Hargreaves, 1994; see equation (1)) to calculate potential evapotranspiration.

$$PET_m = 0.0023\, Ra_m\, (T_m + 17.8)\, (T_{max,m} - T_{min,m})^{0.5} \quad (1)$$

where PET_m is the potential evapotranspiration (mm) in a given month m; Ra is the extraterrestrial radiation, which depends on latitude and latitude; T_m is the monthly mean temperature; $T_{min,m}$ is the monthly average minimum temperature; and $T_{max,m}$ is the monthly average maximum temperature.

2.4. Generalized Linear Models (GLM)

Generalized Linear Models are an extension of linear models able to deal with non-normal distributions of the response variable such as Poisson, binomial, negative binomial, and gamma (Nelder and Wedderburn, 1972). Generalized Linear Models are a widespread approach in many research fields and also in fire science being logistic regression one of the most popular approaches in occurrence modeling (Bar Massada et al., 2012; Chuvieco et al., 2010; Costafreda-Aumedes et al., 2017; Ferreira-Leite et al., 2016; Martínez et al., 2009; Padilla and Vega-García, 2011; Vega-Garcia et al., 1995).

We explored 1000 GLM-logistic models for each combination of period-season-cause-size. These models were created resampling the absence values sample (0) in the construction of the dependent variable. We randomly selected as many absence grids as presence grids (1) do exist on a given occurrence subset, to then construct the corresponding dependent variable. The resulting models allowed (i) to determine which variables were significant ($p < 0.05$) and (ii) examining whether the spatial location of absence values was influencing variable performance. Overall, if a variable was significant in at least 25% of the models (250 times) it is selected as candidate for the final GWR models.

2.5. Geographically Weighted Logistic Regression (GWLR)

Geographically Weighted Regression is a spatial-explicit statistical technique considered as a spatial disaggregation of global regression models. Geographically Weighted Regression extend global regression

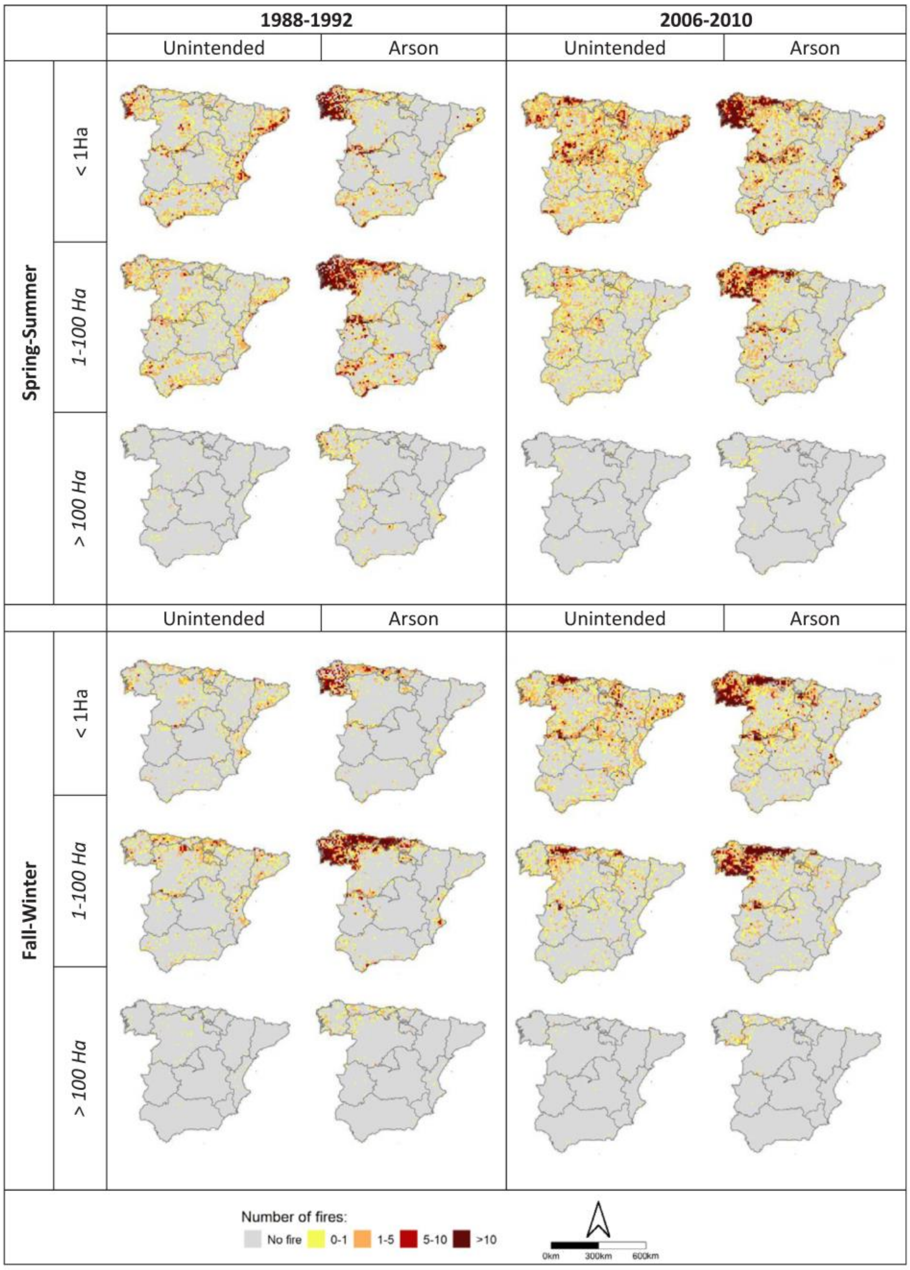

Fig. 2. Spatial distribution of wildfire occurrence.

models allowing to calibrate sets of spatially limited models, thus yielding local regression outputs (Fotheringham et al., 2002). Such modeling often outperforms global regression models as well as enables further interpretation of the analyzed phenomena. Same as their global counterpart, GWR models produce several statistical outputs such β regression coefficients and significance tests but, rather than a single set of statistical parameters, we obtain a collection of parameters for each location apiece; thus allowing to account for the spatial variability in the predictors. A conventional GWR model is described as follows (Fotheringham et al., 2002):

$$y_i = \sum_k \beta_k (u_i, v_i) x_{k.i} + \varepsilon_i \tag{2}$$

where y_i, $x_{k,i}$ and ε_i are, respectively, dependent variable, k_{th} independent variable, and the Gaussian error at location i; (u_i,v_i) is the X/Y coordinate of the i_{th} location; and coefficients β (u_i,v_i) are varying depending on the location.

Logit GWR (Geographically Weighted Logistic Regression or GWLR) was applied to each occurrence subset of period, season, cause, and fire size. Model fitting was conducted using optimized *Adaptive Bisquare Kernel* bandwidth (according to the Corrected Akaike Information Criterion) considering all predictors as local covariates (see Nakaya et al. (2009) for additional specifics on the method). For each subset we adjusted 20 different models using the same resampling procedure described in the GLM section. The calibration of the GWLR models include a *Leave-one-out* cross-validation procedure (LOOCV). Outputs from the LOOCV were used to compute the area under the Receiver Operating Characteristic (ROC) curve (AUC), a threshold-independent approach to determine and compare the performance of binary models (Hanley and McNeil, 1982).

Contrary to Gaussian GWR models, GWLR can only deliver predictions in measured locations, i.e., those points that make up for the dependent variable (Fotheringham et al., 2002; Nakaya et al., 2009). Following a similar approach to that by Rodrigues et al. (2014) or Song et al. (2017), t-values from each model were spatialized using exact interpolation methods (Inverse Distance Weighting). This produces a set of 20 raster maps of t-values per covariate and occurrence subset. To analyze the results and thus provide insights into the spatial-temporal changes of variable contribution, t-values from each set of maps were aggregated according to the median. In addition, the absolute deviation to the median (MAD) was computed to provide a measure of the dispersion or uncertainty of the results (Leys et al., 2013). In this way, the spatial distribution of the central t-value and its dispersion-uncertainty were addressed.

In this work we explored 24 subsets of fire occurrence combining two time periods (1988–1992 and 2006–2010); two human-related ignition sources (negligence/accident and arson); two seasons (summer-spring and winter-fall); and three fire size intervals (< 1 Ha, 1–100 Ha and > 100 Ha). A set of 8 triggering factors (7 human-related and 1 climate-related) were selected and tested. For each occurrence subset 20 GWLR models were constructed and then averaged using the median. Every single covariate was then examined in terms of its spatial pattern of significance according to the Student's t values of the β coefficients. The temporal framework was selected on the basis of Rodrigues et al. (2016), considering data limitations. Fire records were only fully reliable since 1988 (Vélez, 2001) whereas climate data were only available until 2010 (Gonzalez-Hidalgo et al., 2015; González-Hidalgo et al., 2011).

All predictors (both human and climate; see section 2.3) were spatialized using a 10 × 10 km reference grid. Human-related variables were adapted to the study periods 1988–1992 and 2006–2010. Specifically, we used Corine Land Cover maps 1990 and 2006; and data on Demographic Potential corresponding to 1991 and 2006. In this way, we account for time-specific settings of the explanatory factors which may differ from one period to another due to socioeconomic changes. Additionally, predictors were submitted to collinearity analysis and were found to be independent (Variance Inflation Index < 4; Fox and Monette, 1992).

Data manipulation, model calibration, validation, plotting and mapping (except maps corresponding to the study area which were elaborated with ArcGIS 10.5) were developed using the R software for statistical computing (R Core Team and R Development Team Core, 2017) packages: *GWmodel* for GWLR modeling, *gstat* for data interpolation, *car* for multicollinearity assessment, *dismo* for bootstrapping and accuracy assessment, *spei* to calculate the Standardized Precipitation-Evapotranspiration index, *ggplot2* and *lattice* for mapping and plotting, *raster, rgdal* and *sp* for spatial data manipulation and *parallel* for parallel computing for model development.

3. Results and discussion

3.1. Contribution of driving factors across occurrence subsets

Table 2 summarizes the results from GLM variable selection. Overall, no variable was significant ($p < 0.05$) in all occurrence subsets apart from SPEI. Power lines and railroads, are the next predictors in terms of participation, appearing 18 times, followed by WAI and WUI (14 times each), forest tracks (13 times), natural protected areas (12 times) and, finally, demographic potential (10 times).

From the ‘occurrence subset' point of view, there is great variability in the effective number of predictors. In general lines, subsets of small fires require more predictors than those considering large fires. Subsets covering medium-size fires are somewhat in-between, although closer to small fires'. There is no evident difference in the number of predictors amongst ignition source or period. However, some predictors do have some ‘preference' towards a specific occurrence subset. The Wildland-Agricultural interface is more frequently selected in fall-winter (9 times). The Wildland-Urban interface appears more often in spring-summer (9 out of 14 times selected). Natural protected areas, despite being one of the predictors with less appearances, is most frequently select in present models (9 out of 12 times selected). Power lines, railroads and forest tracks do not show any preference, being present in most subsets. Again, SPEI is selected in all subsets.

3.2. Spatial and temporal patterns of wildfire driving factors

Figs. 3–10 display the spatial pattern of the significance ($p < 0.05$, 0.01, 0.001) and explanatory relationship (either positive in brown; or negative in green) of the covariates. Point size is used to represent uncertainty –MAD– in the predicted value. Large points vary less than 20% (low); medium-size points vary between 20 and 50% (medium); and small points vary over 50% (high) around the median.

Several works report a strong contribution of WAI to human-caused fires in Spain. Rodrigues et al. (2014a) investigated WAI's influence on fires over 5 ha burned in the period 1988–2011. They reported strong positive relationships all over Spain. Rodrigues and de la Riva (2014a) reported similar results. In the same line, other works (Chuvieco et al., 2010; Martínez-Fernández and Koutsias, 2011) reached similar conclusions. However, we detected a strong variability in the contribution of WAI across subsets (Fig. 3). This may imply that the explanatory power of WAI may depend on fire size, season or time period. Rodrigues et al. (2016) suggest WAI might be losing performance over time because of forest management policies such as investment in social intervention programs in rural. According to our results WAI seems to be mostly related to small and large unintended fires during summer-past subsets. It also displays a positive relationship with small and large fall-winter fires during the past all over the north region, also observed in arson fires. Moving towards present WAI loses performance as a fire occurrence driver during spring-summer except for large unintended fires in the Southern Mediterranean region. In addition, WAI shows a strong positive relationship with large fall-winter arson fires in North-west.

Overall, we can observe a stronger relationship with fall-winter fires that increases towards present days, in terms of significance and reduced uncertainty in the prediction. However, WAI losses performance during spring-summer months. Fall-winter fires in Spain are mostly intentional; up to 80% of them are linked to livestock burnings for the maintenance of pasture (Ganteaume et al., 2013; Leone et al., 2003). Fire has been traditionally the preferred means to eliminate agricultural residues, weeds or cleansing field's margins from hedges and shrubs. The increase in the contribution of WAI during winter-fall may be promoted by increased mechanization efficiency (Leone et al., 2009), burn disposal of agricultural byproducts (only allowed during this season).

Wildland-Urban Interface (Fig. 4) has been commonly considered the most relevant human ignition indicator (Galiana-Martin et al., 2011; Martínez et al., 2009; Romero-Calcerrada et al., 2010; Vilar et al., 2016). In the early 90s WUI is clearly related to small-medium unintended and, to a lesser extent, arson fires. Like WAI, the contribution of WUI to fire occurrence towards present days was expected to drop. While this might be the case for spring-summer fires is not happening during fall-winter. A recent study by Modugno et al. (2016) indicate that “*the probability of large burned surfaces increases with diminishing WUI distance in regions with a strong peri-urban component as Cataluña, Comunidad de Madrid, Comunidad Valenciana*”. Our results suggest the WUI appears to gain performance to explain fall-winter small fires, being significant in all the study area in unintended and arson fires in models for 2006–2010. In any case, the discrepancies between the studies may be linked to the difference in the scale of analysis (European *vs* national) or the spatial unit of analysis (NUTS 3 *vs* 10 × 10 km grid).

Additionally, some areas in the south are significant both in past and present medium arson fires, with the significant-positive area growing towards present. Therefore, WUI displays a stronger relationship during spring-summer in the past that shifts towards fall-winter in present years. Decreased contribution of WUI during spring-summer can be understood as a more sensible behavior of human beings in

Table 2
Summary of variable significance ($p < 0.05$) across subsets from GLM. Number of selected variables reported between parentheses. Bold font indicates variables significant in GWLR. Effective number of parameters in GWLR models reported between brackets. WAI: Wildland-Agricultural interface; WUI: Wildland-Urban interface; DPT: Demographic potential; PWL: power lines; RRD: railroads; TRK: forest tracks; NPA: natural protected areas; SPEI: Standard Precipitation-Evapotranspiration index.

		1988–1992		2006–2010	
		Unintended	Arson	Unintended	Arson
Summer	< 1Ha	***WAI***, *WUI*, ***DPT***, *PWL*, *RRD*, ***SPEI*** *(6)[3]*	***WAI***, ***WUI***, ***RRD***, *TRK*, ***SPEI*** *(5) [4]*	***WUI***, ***DPT***, ***PWL***, *RRD*, ***TRK***, ***NPA***, ***SPEI*** *(7) [6]*	***WUI***, ***PWL***, ***RRD***, ***NPA***, ***SPEI*** *(5) [5]*
	1-100 Ha	*WUI*, ***PWL***, ***RRD***, ***SPEI*** *(4) [3]*	***WAI***, ***WUI***, ***PWL***, ***RRD***, ***TRK***, ***SPEI*** *(6) [6]*	***WUI***, *PWL*, ***RRD***, ***TRK***, ***NPA***, ***SPEI*** *(6) [5]*	***PWL***, ***RRD***, ***SPEI*** *(3) [3]*
	> 100 Ha	*WAI*, ***WUI***, ***PWL***, ***TRK***, ***SPEI*** *(5) [4]*	***WUI***, ***DPT***, ***RRD***, ***TRK***, ***SPEI*** *(5) [5]*	***WAI***, ***DPT***, *PWL*, ***SPEI*** *(4) [3]*	***DPT***, ***PWL***, ***TRK***, ***SPEI*** *(4) [4]*
Winter	< 1Ha	***WAI***, ***WUI***, ***RRD***, *TRK* *(5) [3]*	***WAI***, ***RRD***, *TRK*, ***NPA***, ***SPEI*** *(5) [4]*	*WUI*, *PWL*, *RRD*, ***NPA***, ***SPEI*** *(5) [2]*	***WAI***, *WUI*, ***DPT***, ***PWL***, ***RRD***, ***TRK***, ***NPA***, ***SPEI*** *(8) [7]*
	1-100 Ha	***PWL***, ***NPA***, ***SPEI*** *(3) [3]*	***WAI***, ***WUI***, ***DPT***, ***PWL***, ***RRD***, ***NPA***, ***SPEI*** *(7) [7]*	***WAI***, ***DPT***, *PWL*, *RRD*, ***TRK***, ***NPA***, ***SPEI*** *(7) [5]*	***WAI***, ***WUI***, ***PWL***, ***RRD***, ***TRK***, ***NPA***, ***SPEI*** *(7) [7]*
	> 100 Ha	***WAI***, ***DPT***, ***PWL***, ***RRD***, ***SPEI*** *(5) [5]*	***WAI***, ***SPEI*** *(2) [2]*	***WAI***, *TRK*, *NPA*, ***SPEI*** *(4) [2]*	***DPT***, ***PWL***, ***RRD***, ***NPA SPEI*** *(5) [5]*

forest areas, thus as an increased concern about the environment. One of the cornerstones of fire prevention in Spain are awareness campaigns and other educational resources, which might be ultimately behind the observed behavior in WUI during spring-summer (article 44, Ley 43/2003, de 21 de noviembre, de Montes).

Demographic potential (Fig. 5) is a variable linked to increased pressure of human beings on wildlands. However, opposite to WUI, DPT relates to urban areas rather than rural settlements and residential areas (Calvo and Pueyo, 2008; Rodrigues and de la Riva, 2014a; Rodrigues et al., 2016). Demographic potential shows positive relationship in small-unintended past fires alone. The remaining combinations are either non-significant or significant negative. The only exception is a small region in NW for arson fall-winter fires in recent years. Considering this, we can conclude urban population is not an effective driver of wildfires. In previous works, changes in DPT were reported as a strong driver (Rodrigues and de la Riva, 2014a, 2014b), but used as a standalone value DPT no longer contributes as a fire occurrence driver. It was somehow related to small unintended fires in past subsets, but currently appears as a deterrent factor, i.e., fires do not occur near purely urban areas.

According to Fig. 6, PLW Increases performance towards present. Power lines are expected to be linked with unintended fires (Leone et al., 2003, 2009). They are usually related with accidental fires from sparks or lightning-bolt arcs reaching vegetated areas. We do observe a more consistent relationship of PWL and small unintended fires in past and medium-size in present. But significant relationships with arson fires are also detected, especially in models from 2006 to 2010. There is no clear explanation to this. It maybe that in some cases the corridors surrounding power lines are used as pathways leading to forest areas or that arsonists try to conceal intentional fires as unintended by starting fires in the neighborhood of power lines. On the other hand, why is the influence of PWL increasing? There are several reasons why power lines cause forest fires. The main one is the contact between vegetation and powerlines, either by directly touching or by fall of the towers or posts. Less frequent is the short circuit in stations or substations and transformers. Similar to fires triggered close to railways, the number of fires related with power lines appears to increase (MAPAMA, 2012; WWF, 2005) due to the lack of maintenance (cleansing) of vegetate areas around lines (WWF, 2005). Depending on the voltage, a buffer 45–100 m wide must be cleared (Ferrer, 2012).

Railroads behave mostly the same as power lines do (Fig. 7). The fact that most railroads depend on an electric power line source makes them like ordinary power lines. But, RRD are also associated mainly with accidental fires. For instance, hot coal transported in semi-open wagons may lead to fire ignitions. But while it is true that locomotives and wagons have been modernized, how is it that the ignition relationship increases instead of decreasing? The answer must be sought in two main aspects. On the one hand, improvement in infrastructure has not reached second-order or old railways, especially those crossing mountain areas. Secondly the lack of cleaning and maintenance of vegetation –especially herbaceous and grasslands– in zones around railways, where sparks, generally coming from the braking, generates potential ignition sources when the environmental conditions are favorable (WWF, 2005).

Forest tracks are a proxy for accessibility to forest areas. Locations and forest enclaves easy to reach are prone to fire occurrence; in particular, arsonist leverage accessibility to forest (Leone et al., 2003). According to Fig. 8, TRK is related to arson fires during past-spring-summer models, and to small fires during winter. Same as other factors depicting human pressure on wildlands (WUI), TRK losses importance towards present, even becoming negative related, i.e., fires tend to occur far from forest tracks, except for unintended large fires, perhaps due to increased recreational use of forest areas (MAGRAMA, 2014).

It is commonly agreed areas under any kind of protection or special management are expected to experience lower fire occurrence, given the extra effort to prevent or suppress fires (Chuvieco et al., 2010). In this sense, NPA (Fig. 9) acts as a deterrent factor associated to increased concern about the environment. Bearing this in mind, NPA should display negative relationships (Leone et al., 2003). Fig. 8 shows non-significant relationship during past-spring-summer models, becoming an actual deterrent factor towards present days, but only in small and medium size fires. Overall NPA gains significance towards present as a restraining driver (Rodrigues et al., 2016). However, it is noteworthy its positive relationship with arson fires in the Northwest region, possibly due to conflicts with new management in protected areas (Hovardas, 2012) or even arsonist targeting valuable resources.

The Standardized Precipitation-Evapotranspiration index (Fig. 10) is the only factor selected as potential driver in every single subset according to the GLM simulations (Table 2). However, same as other factors, its contribution in GWLR models is not always found significant. SPEI has been previously explored in models of burned area size Europe (Camiá and Amatulli, 2009; Piñol et al., 1998; Trigo et al., 2016; Turco et al., 2013; Urbieta et al., 2015). In fact, our results suggest stronger relationship with large fires. To our knowledge there is no prior analysis of SPEI as an ignition or occurrence driver, at least in Spain. Overall, SPEI shows negative relationship (the higher the drought the higher the probability of occurrence) with occurrence, both during fall-winter and spring-summer. In turn, SPEI's influence seems to increase towards present. For instance, models for spring-summer large fires arouse SPEI as significant driver in 2006–2010 but not during

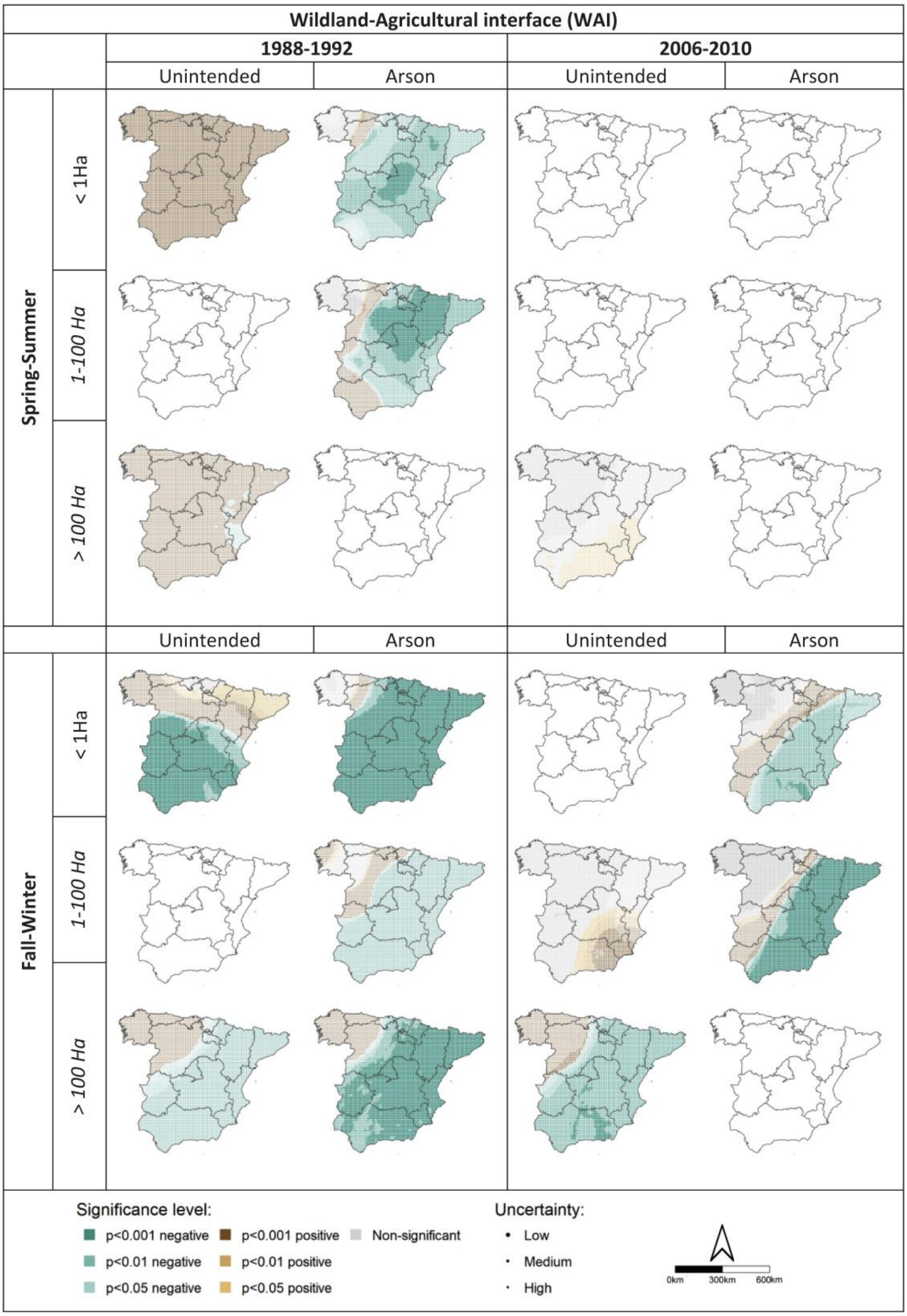

Fig. 3. Spatial pattern of significance level and explanatory sense of WAI. Blank maps indicate no contribution. Dot color represents significance level and explanatory sense. Dot size represents the level of uncertainty according to MAD.

1988–1992. One of the most streaking results is SPEI's influence during winter. Fall-winter conditions are usually considered as unfavorable when it comes to fire triggering. We are aware that our SPEI is calculated using a long temporal span (60 months) but apparently drought anomalies also influence fall-winter fires to a certain degree maybe due to the increased length of the main fire season (Jolly et al., 2015).

3.3. Implications in wildfire modeling

Most models dealing with human-caused fire occurrence are based on large historical datasets, often disregarding fire size or motivation (Chuvieco et al., 2012; Martínez et al., 2013, 2009; Rodrigues and de la Riva, 2014b; Rodrigues et al., 2014; Vilar et al., 2016). However,

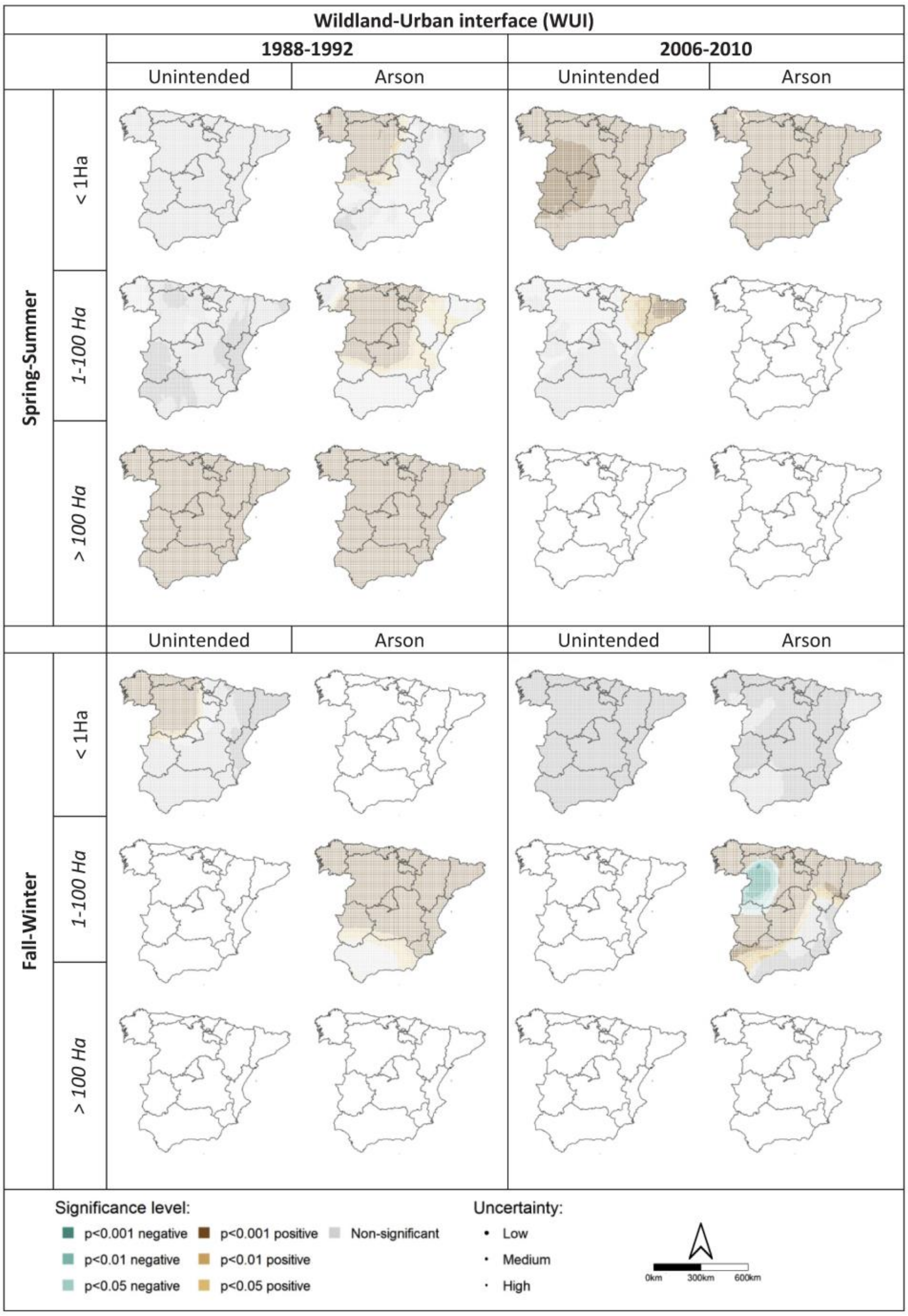

Fig. 4. Spatial pattern of significance level and explanatory sense of WUI. Blank maps indicate no contribution. Dot color represents significance level and explanatory sense. Dot size represents the level of uncertainty according to MAD.

according to the literature there is a clear difference in drivers of natural, accidental and arson fires (Leone et al., 2003). Our results suggest differences in the contribution of the analyzed drivers across the modeled subsets of size, season, and cause. These are usually put together when modeling fire occurrence. Bearing in mind the noticeably differences reported in this study, doing so might not be the best practice, at least when the main goal is investigating the relationship among occurrence and factors. For instance, WAI is largely related to small spring-summer fires and strengthens its role in fall-winter fire occurrence.

From a predictive standpoint, we also find differences in the performance of models. Fig. 11 shows a summary of the AUC from the Leave-one-out cross-validation. As we can see, performance varies according size, season and period. Overall, we find lower performance towards 2006–2010 particularly high in large fires. In addition, fall-winter models tend to perform best, especially in large fires. Moreover, models of arson fires slightly outperform those of unintended fires.

3.4. Implications for forest management

According to Badia et al. (2002) forest fire policy overreacted to the waves of wildfires during the 90s, overemphasizing suppression to the detriment of prevention; but over the years, the balance between suppression and prevention is slowly accomplished (MAPAMA, 2012). In fact, prevention measures appear to be working to a certain degree given the overall drop in the explanatory performance of WUI and WAI (Fox et al., 2015; Rodrigues et al., 2016), two of the most important variables associated to wildfires in Spain (Martínez et al., 2009, 2004b; Rodrigues et al., 2014) and Mediterranean environments (Vilar et al., 2016). For instance, there is investment in social intervention programs

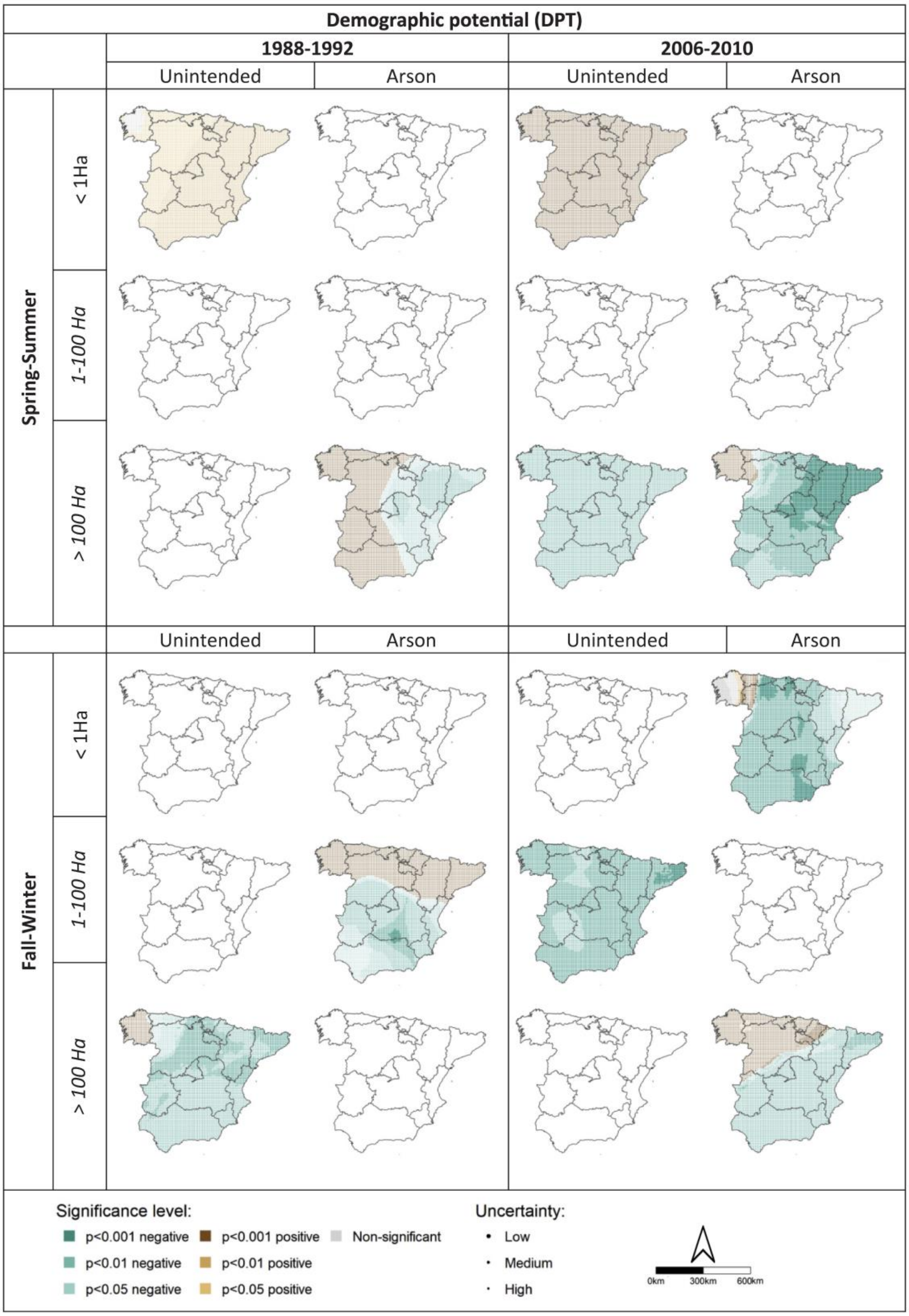

Fig. 5. Spatial pattern of significance level and explanatory sense of DPT. Blank maps indicate no contribution. Dot color represents significance level and explanatory sense. Dot size represents the level of uncertainty according to MAD.

in regions with high percentage of fires triggered by accidents due to the use of fire in rural districts of Asturias, Cantabria, Castilla y León or Galicia. Notwithstanding, it is necessary to go a step further and actively involve those clusters of individuals most associated with high accident rates (WWF/Adena, 2016).

On the other hand, climate plays a determinant function, which appears to grow towards present (Fig. 10). According to Rodrigues et al. (2016), models disregarding environmental conditions steadily loss performance over time. In this work, we identified SPEI as one of the most important indicators of fire occurrence. Indeed, it is better found in large fire models (Camiá and Amatulli, 2009; Piñol et al., 1998; Trigo et al., 2016; Turco et al., 2013; Urbieta et al., 2015) but, in any case,

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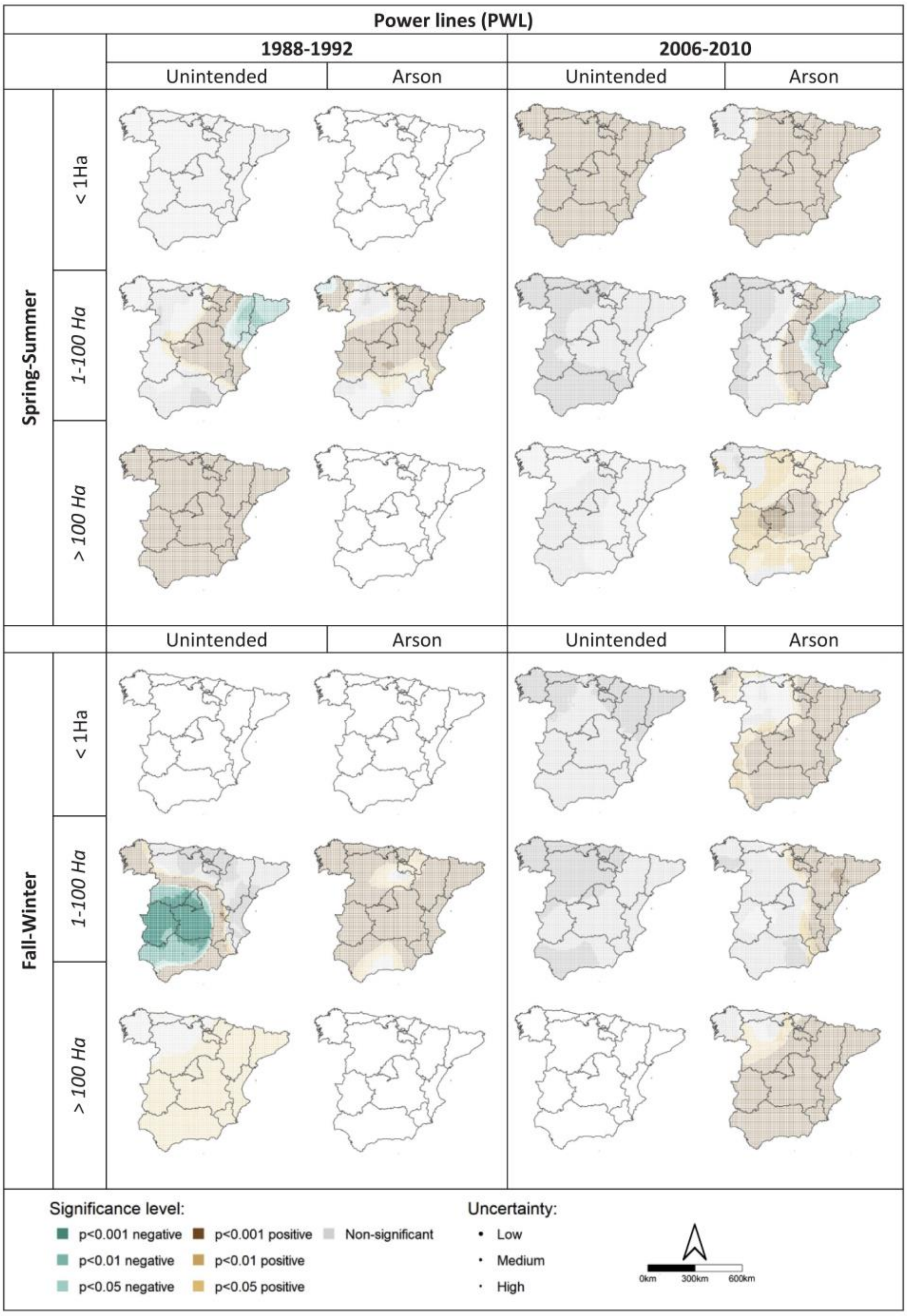

Fig. 6. Spatial pattern of significance level and explanatory sense of PWL. Blank maps indicate no contribution. Dot color represents significance level and explanatory sense. Dot size represents the level of uncertainty according to MAD.

SPEI is also linked to the occurrence of small and medium fires. This suggests climate not only influences ignition in the usual way (the drier the likelier to trigger) but also arsonist may be targeting favorable conditions for fire ignition. In this regard, it is noteworthy the contribution of SPEI to fall-winter fires. Fall-winter is a season theoretically unfavorable to fire ignition, but with persistent dry conditions fires can occur and become uncontrolled (WWF, 2005). For instance, 2015 and 2017 were years with intense fall-winter fire activity tied to an extended dry period after summer, thus promoting larger fires (68% of large fires in 2017 triggered during fall-winter; ADCIF, 2017), matching the expected lengthening in fire season according to Jolly et al. (2015). Therefore, management strategies must encourage compelling considerations for fall-winter fires. For instance, the policy managing burning permits for plot cleansing and maintenance must be revised. It should target promoting a different strategy for the removal of agricultural residues (centralized dumping and disposal; use as soil fertilizer or biomass). Moreover, forest fire crews and on watch personnel must be active thorough most of the year and not only during the main fire season, i.e., spring-summer months (Costafreda-Aumedes et al., 2018).

Finally, natural plus unintended fires account for less than 50% of fires in Spain (Table 1), with the remaining proportion of fires attributed to arson fires. Fire cause is usually neglected or disregarded in most fire modeling approaches given the challenge that poses associating arson motivations to traditional fire drivers (Leone et al., 2003; Martínez et al., 2009, 2004a; Rodrigues et al., 2016). Nonetheless, little is known about the actual motivations or factors around arson wildfires. For instance, the European fire database lists as unknown the deliberately started fires reported from the Spanish database compiled in the European Forest Fire Information System, due to the lack of detail on

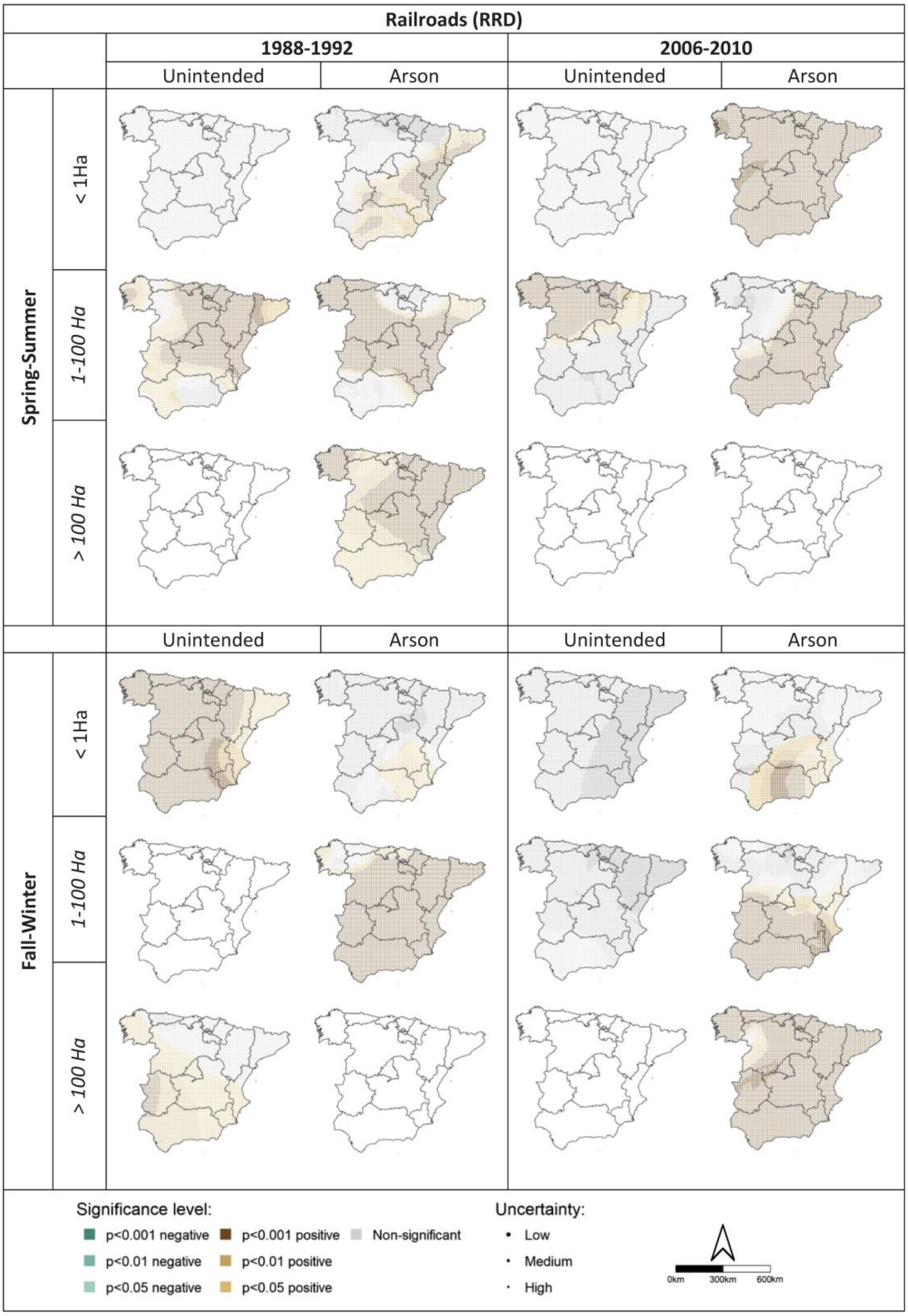

Fig. 7. Spatial pattern of significance level and explanatory sense of RRD. Blank maps indicate no contribution. Dot color represents significance level and explanatory sense. Dot size represents the level of uncertainty according to MAD.

motivations (Camia et al., 2013). Intentional fires have grown in number towards present, particularly during fall-winter season. They appear to be associated to areas close to residential areas in forest enclaves (WUI) during spring-summer and somehow related to infrastructures such as railroads and powerlines which might be indirectly providing accessibility. Moreover, large arson fires in the present are positively related to NPA which suggest arsonist try to burn valuable recreational resources.

4. Conclusions

In this work we explore past and present subsets of fire size, cause

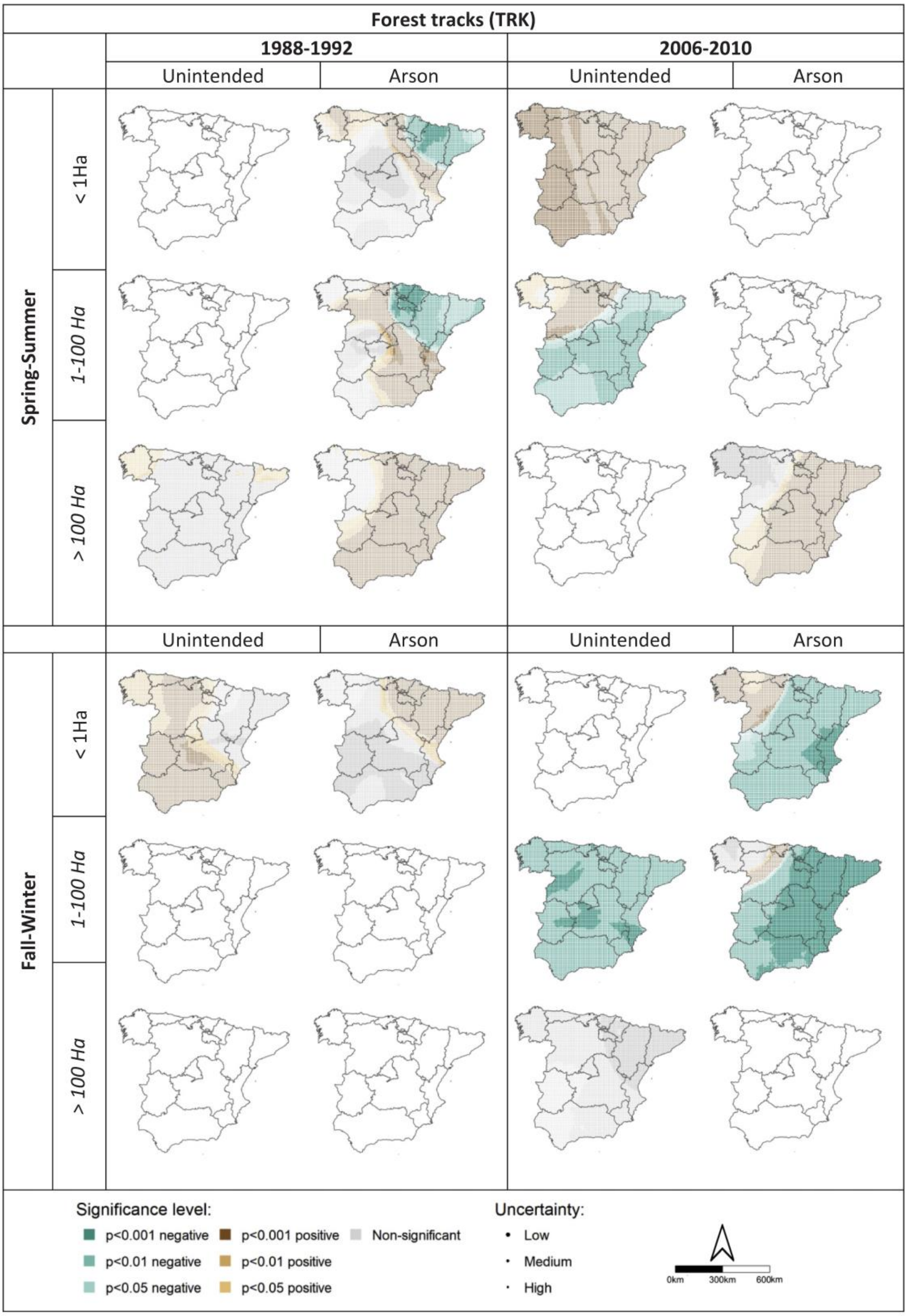

Fig. 8. Spatial pattern of significance level and explanatory sense of TRK. Blank maps indicate no contribution. Dot color represents significance level and explanatory sense. Dot size represents the level of uncertainty according to MAD.

and season to determine whether fire triggering of wildfires factors vary depending on fire features and time. The study is developed using GWLR to integrate insights into underlying spatial patterns into the temporal perspective.

Our results confirm the non-stationary nature of wildfire drivers in Spain. Results suggest that temporal and spatial differences in fire features do exist. For instance, intentional fires in present models are no longer related to accessibility. Moreover, arsonist might be now targeting favorable climate conditions according the SPEI outputs. In the same line, human-related factors are losing performance towards present days in favor of climate-related drivers.

From a modeling perspective, considering fire events altogether

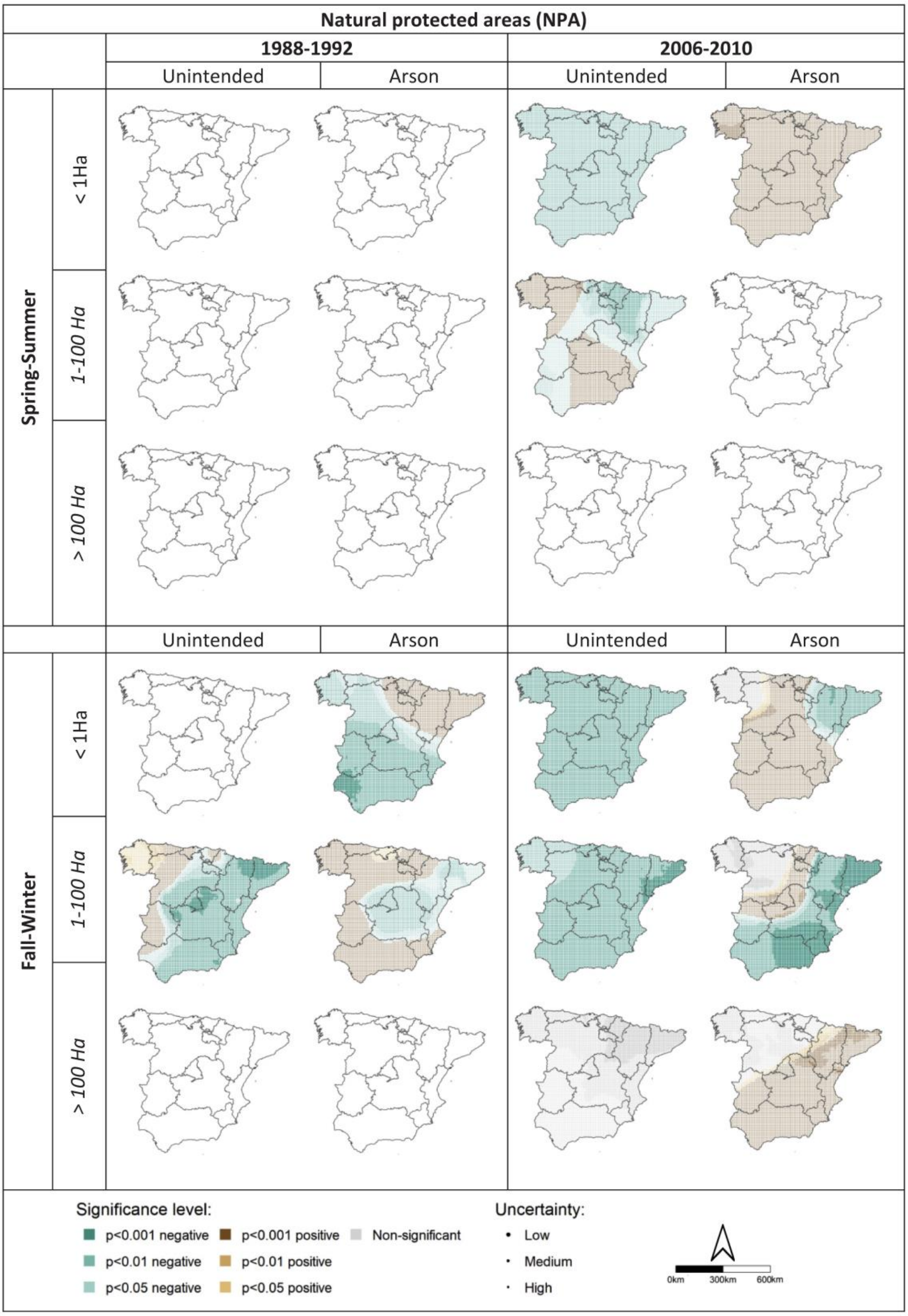

Fig. 9. Spatial pattern of significance level and explanatory sense of NPA. Blank maps indicate no contribution. Dot color represents significance level and explanatory sense. Dot size represents the level of uncertainty according to MAD.

disregarding fire features (season, cause and size) is not fully recommended. The behavior of fire drivers not only evolved temporally but varies as well across the analyzed subsets of occurrence.

Finally, management policies should be adapted to reflect the different behavior observed in the subsets. Moreover, considering the increasing importance of climate-related drivers, activities targeting fuel management and preventive silviculture must be encouraged. On the other hand, the loss of performance of human-related factors might be reflecting the success of prevention measures during the study period.

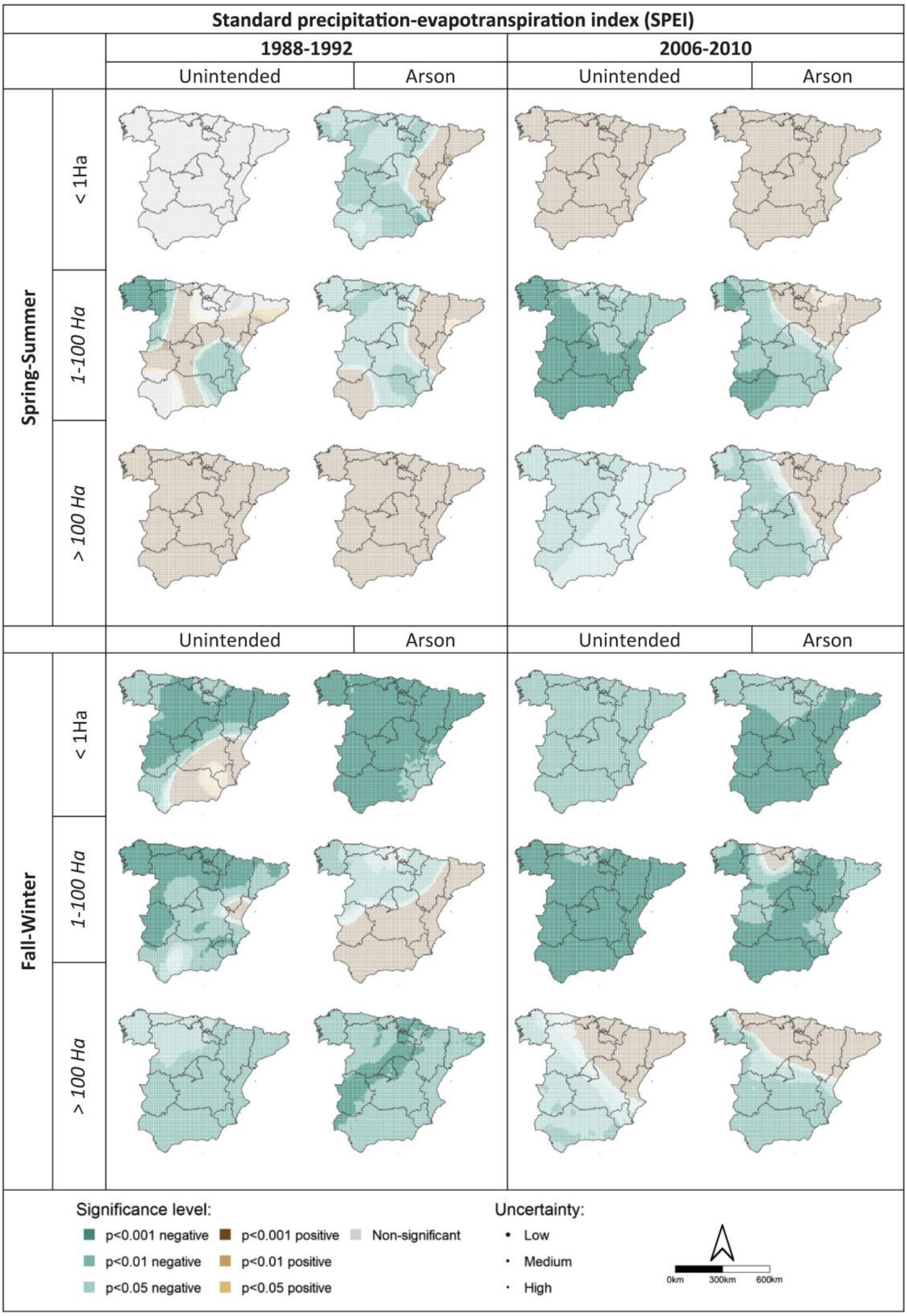

Fig. 10. Spatial pattern of significance level and explanatory sense of SPEI. Blank maps indicate no contribution. Dot color represents significance level and explanatory sense. Dot size represents the level of uncertainty according to MAD.

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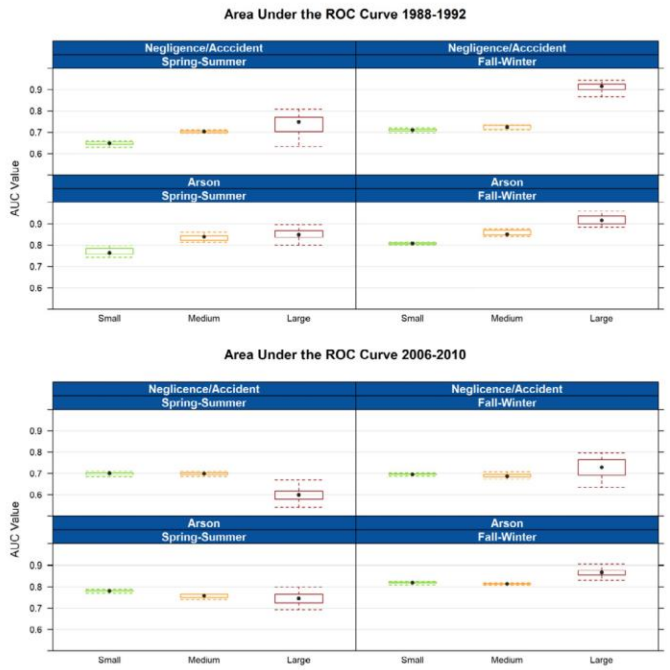

Fig. 11. Predictive performance according to the Area Under the Receiver Operator curve.

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8

CHAPTER 8: EVOLUTION AND CAUSES OF FIRE REGIME CHANGE

This chapter describes the main results, discussion and conclusions of the outlining of fire regime zones, their temporal evolution towards the near future and the analysis of the influence of drivers of fire activity in the observed fire regime trajectories. Random Forest is employed to evaluate the individual contribution of each fire driver, as well as, ARIMA models are used to forecast the immediate future trend of the main fire regime features.

Fire regime dynamics in mainland Spain. Part 1: drivers of change

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Abstract
Fire regimes are evolving worldwide driven by socioeconomic and environmental changes. Understanding the forces behind fire regime dynamics is essential to achieve effective wildfire management and policymaking. The current research belongs to a series of two manuscripts aimed at describing spatial-temporal dynamics of fire regime and its drivers in mainland Spain. In this work, we identified the main transitional pathways of fire regime zones between past (1974-1994) and current (1995-2015) conditions to identify the influence of the main wildfire drivers (demographic potential, climate trends, forest interfaces and topography). Our methodology combined Principal Component Analysis and Ward's hierarchical clustering to identify and spatialize homogenous regions of fire regime on the basis of the main fire regime features: number of fires, burned area, burnt area from lightning-caused fires, area affected by large fires (>100 ha) and seasonality. This procedure was replicated in current and past conditions to extract the most frequent combinations of fire regime typologies, eventually leading to a set of binary response variables (change versus persistence of fire regime). Finally, Random Forest regression was applied to estimate the explanatory performance of fire regime drivers for each transition path.

Our results point to an overall decline in fire activity over most of the Spanish territory. The hinterlands and Mediterranean coast experienced the greatest decrease in fire activity. In contrast, winter activity has progressed in the North-western region. According to Random Forest outputs, demographic potential highlights as the main driver of fire regime change (both regressive and progressive), followed by climate dynamics (temperature and rainfall trends) and topographic features. In turn, Wildland-Agricultural Interface (WAI) and Wildland-Urban Interface (WUI) were also behind several noticeable trajectories as is the case of winter fire progression (WAI) or moderate increase in fire incidence linked to human-caused fires (WUI).

Keywords: Forest fires, fire regime, fire features, wildfire drivers, Random Forest, suppression policy

1. INTRODUCTION

Fire regime is usually defined as the average conditions of wildfire that are persistent and consistent within a particular region and over a given period (Krebs et al., 2010). Its inception depends on the confluence of various factors, i.e., climate, humans, fuel and ignition cause (Curt and Frejaville, 2018). Human beings have coexisted with fire during millennia, leveraging it as a tool to modify the landscape to their own needs (Pyne, 2009; Wagtendonk, 2009). In human-dominated landscapes, the extensive use of fire has altered the once natural fire regime transforming it into an anthropogenic one. During the second half of the 20th century, the confluence of cropland abandonment in remote areas (promoting fuel accumulation) with the increased presence of human activities in the wildlands led to a sudden increase in fire activity in some Mediterranean countries such as Portugal or Spain (MAPAMA, 2017) and, thus, a growing interest in forest fire research (Leone et al., 2003a; J G Pausas and Vallejo, 1999; Piñol et al., 1998). However, ever since the extraordinary fire waves during the mid-90s a total fire exclusion policy was implemented (Moreno et al., 2014), leading to the progressive decline in fire activity (Jiménez-Ruano et al., 2017; Silva et al., 2019) and altering the contribution of human factors (Leone et al., 2003a; Vittorio Leone et al., 2009). For instance, in Spain agricultural activities seem to be losing significance in explaining fire occurrence over time whereas weather is growing in importance (Rodrigues et al., 2016). Furthermore, fire prevention and suppression have been increasingly funded, reaching a top investment of 78 million € in 2015.

Despite the decreasing fire trends, fire-weather scenarios predict more hazardous conditions, threatening both ecosystems and society (Alcasena et al., 2019; Badia et al., 2011). In this sense, the so-called 'fire paradox' foresees larger fires as a consequence of sustained full fire suppression coupled with fire-prone climate conditions. Humans play a crucial role in shaping the incidence of wildfires acting either as initiators or suppressors, resulting in the alteration of the natural fire regime (Alcasena et al., 2019). The relationship between fire regime and socioeconomic and environmental factors has been addressed in the literature. Pechony and Shindell, (2010) suggested that climate will drive global fire trends to the point of overcoming human influence, and there is already evidence of how climate-driven vegetation change can affect regional-scale fire regimes in Mediterranean type ecosystems (Liu and Wimberly, 2016). Nonetheless, under the current circumstances, housing density and proximity to roads promote human-related ignitions (Clarke et al., 2019; Martín et al., 2019; Rodrigues et al., 2019a) whereas lightning ignitions relate to intra-annual patterns of rainfall (Dickson et al., 2006; Pineda and Rigo, 2017; Wang and Anderson, 2010). In the European-Mediterranean region the main forces behind wildfire incidence relate to the proximity to roads and settlements or the recreational use of forest lands (Ganteaume et al., 2013). Likewise, agricultural activities explain a large fraction of arson and accidental fires (Camia et al., 2013; Rodrigues et al., 2018). Generally, the combination of climate variations, fuels, and human activities what explains the geographical gradients for both human and natural-caused fires (Ganteaume et al., 2013). In this sense, the aggressive fire suppression strategy seems to counterbalance the effects of climate change and human activities (Curt and Frejaville, 2018) to the point of overriding the influence of weather-drought in some relatively humid regions of Portugal (Fernandes et al., 2014). Understanding the spatial and temporal extent of fire regime and the potential drivers fostering their change is essential to identify (and rectify) the ongoing trajectories in fire activity. To date, regional schemes for fire regime zoning in Spain are scarce and few of them deal with the underlying drivers of fire activity. The 'official' fire regime division in Spain was based on gross fire statistics, distinguishing between the Mediterranean coast, the northern Atlantic coast and a wide hinterland region between them (A Cardil and Molina, 2013). However, approaches that are more sophisticated have been developed recently. Some of them leverage the historical fire records alone (Jiménez-Ruano and et. al., 2018; Moreno and Chuvieco, 2013), while others rely on the role of fire drivers (Montiel Molina and Galiana-Martín, 2016; Rodrigues et al., 2019b). However, these studies provide a 'static' picture of fire regimes without taking into account their temporal evolution.

In this work, we developed a workflow to identify and outline the spatial-temporal evolution of fire regimes and investigate the drivers of change. We explored past (1974-1994) and current (1995-2015) fire features using historical fire records from the Spanish fire database (EGIF, Estadística General de Incendios Forestales; MAPAMA, 2015). We combined cluster analysis and random forest regression to a) outline past and current fire regime zones, b) identify and characterize the most frequent transitions and, c) assess the role of drivers in observed trajectories.

2. DATA AND METHODS

The proposed methodology was developed in three stages (see Fig. 1). First, we retrieved historical fire records from the EGIF database and organized them into two separate datasets, one depicting past conditions (1974-1994) and another covering the most recent period (1995-2015. According to Jiménez-Ruano et al. (2017a) and Curt and Frejaville (2017), a major breakpoint in the temporal evolution of fire activity can be found in the mid-90s. Likewise, fire statistics pointed to the year 1994 as one of the worst in terms of fire incidence, especially in terms of large fires (MAPAMA, 2017). Then, we identified fire regime typologies in the current period by means of cluster analysis and projected them into the past using K-Nearest Neighbor (KNN) classification to determine the main fire regime transitions. Finally, we fitted several Random Forest models with the most frequent fire regime transitions (change/no change) against the main fire drivers. All statistical procedures, maps and plots were developed using the R statistical programming language (R Core Team and R Development Team Core, 2017), stats package was used for PCA, NbClust for cluster analysis, knnGarden for past cluster assignation, splitstackshape for KNN validation. Random Forest models were trained and tested using caret (Kuhn, 2008) and pdp packages (Greenwell, 2017).

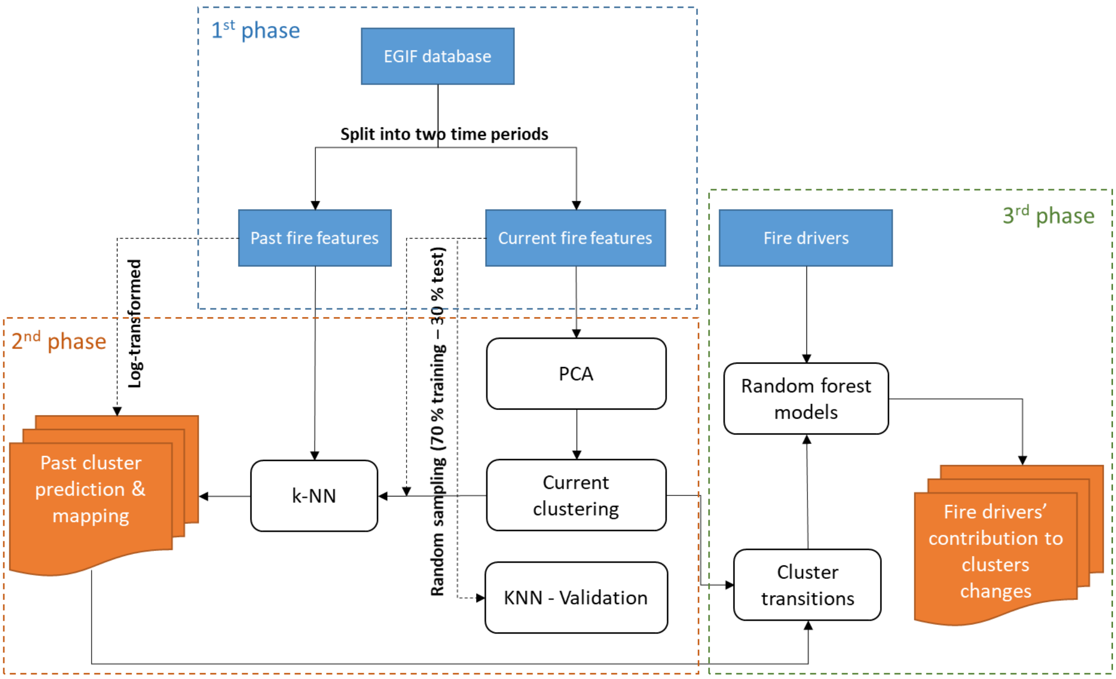

Fig. 1. General workflow of the methodology including input data split, clustering, KNN classification-validation and Random Forest fitting recent cluster transitions and fire drivers.

2.1. Study area

The study area was mainland Spain, a region covering about 498,000 km^2. The region is dominated by a Mediterranean climate extending from the eastern coast to the hinterlands, with Oceanic conditions along the northern coast. The Mediterranean climate characterized by high annual thermal amplitude with hot summers in the inner region and milder conditions along the coast. Precipitation is distributed irregularly over the year, peaking in autumn and spring, with a clear minimum during summer. The driest areas extend across the southeastern region and the Ebro Valley. The Oceanic climate displays milder temperatures thorough the year and high precipitation distributed regularly throughout the year (average values over 1,000 mm). The broad spectrum of vegetation (Fig. 2) within this region ranges from deciduous oak to evergreen oak woodlands (*Quercus robur* L., *Fraximus excelsior L.* or *Fagus sylvatica L.*) although this region is also heavily dominated by forest plantations such as *Pinus radiate D.Don* and *Eucalyptus globulus Labill.* The vegetation in the Mediterranean is characterized by complex mosaics of agricultural systems and plant communities such as sclerophyllous and evergreen vegetation, mainly pine species (*Pinus halepensis Mill.*, *Pinus sylvestris L.*, *Pinus nigra J.F.Arnold*, *Pinus pinea L.* or *pinaster Ait.*) and oak (*Quercus ilex L.* and *Quercus suber L.*) forest. In addition, altitudinal belts do exist along the highest mountain ranges such as the Pyrenees along the French border or Sierra Nevada on the southern Mediterranean coast. These sub-regions host a large variety of tree species that are common in central Europe.

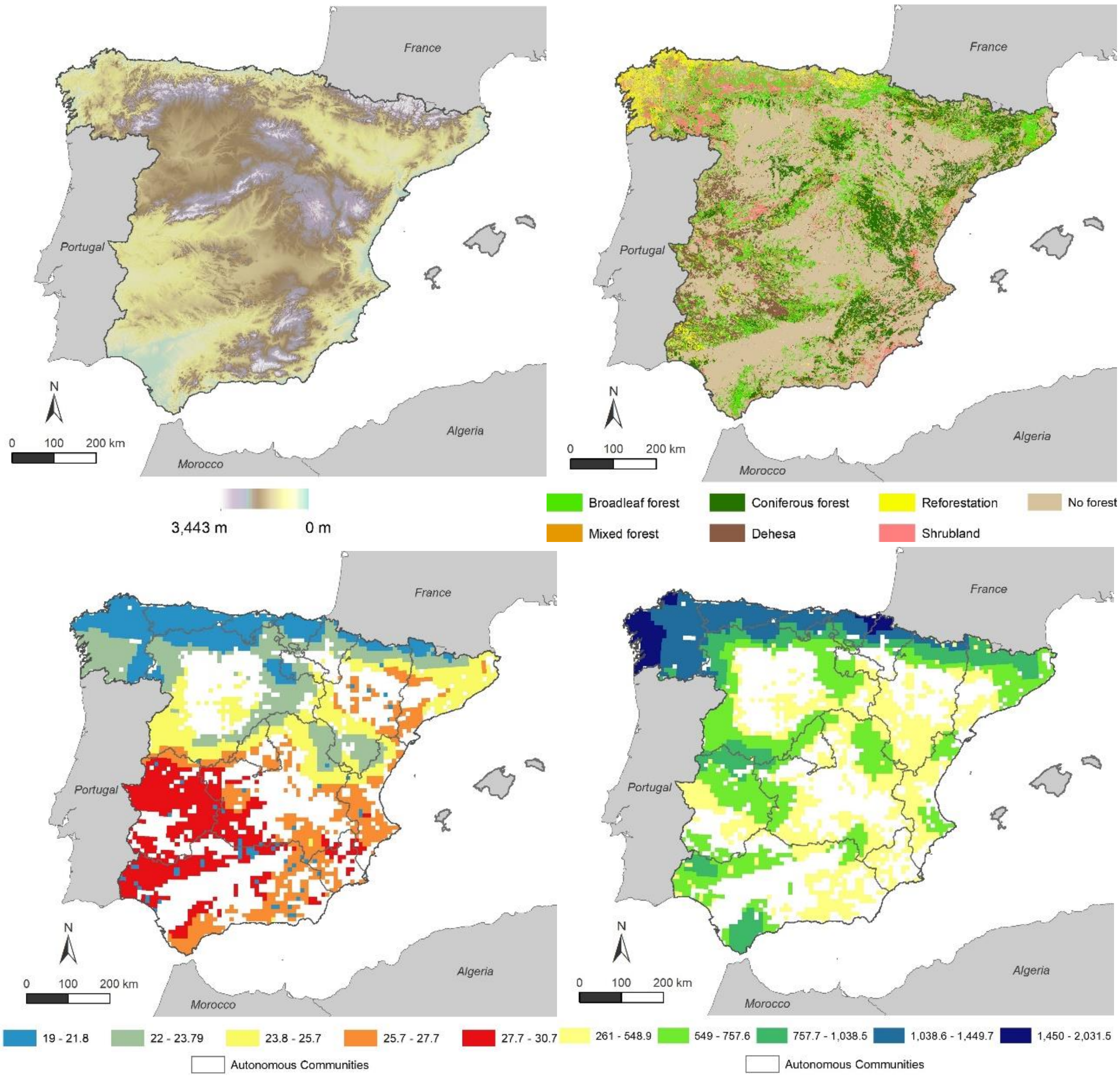

Fig. 2. Elevation map in meters above sea level (top-left), spatial distribution of main forest formations derived from the Spanish Forest Map –MAPA, 2013 (top-right), average annual temperature (bottom-left), and average annual precipitation (bottom-right).

Fires in Spain are mostly related to human activities, with 95% of fire occurrence linked to anthropogenic activities. In turn, natural fires are usually scarce, except for some enclaves around the inner mountain ranges along the Mediterranean coast. Agricultural activities controls fire incidence in the Northwest region, with a traditional use of fire in pasture clearing and stubble burning (Moreno et al., 2014). On the other hand, the Wildland Urban Interface promote fire ignitions in the peri-urban large metropolitan areas.

2.2. Fire data

We computed 5 fire features by grid level (Fig. 3), selected according to existing studies (Jiménez-Ruano et al., 2017b; Moreno and Chuvieco, 2013; Silva et al., 2019):

- **Fire frequency (F):** total number of wildfires per grid and period.
- **Winter frequency (FW):** number of wildfires occurred during autumn-winter (from October to March) by grid and period.
- **Burned area (BA):** total surface burned in hectares of the grid and period.
- **Burned area by large fires (BA100):** burned area by fires greater than 100 hectares by grid and period.
- **Burned area by nature cause (BAL):** surface burned by lightning in the grid and period.

Fire data were acquired from the Spanish fire database (EGIF, Estadística General de Incendios Forestales; MAPAMA, 2015). The EGIF database compiles fire records since 1968, gathering information about the ignition date, fire size, cause and the approximate location of the starting point, among others. We retrieved fire records at 10x10 km grid level in the period 1974-2015, the longer available at the time this work was conducted. Fire events were organized in two separate datasets depicting periods of stable conditions in terms of fire regime features The selected periods were 1974-1994 and 1995-2015 (past and current henceforth). Small fires (less than 1 ha) were disregarded to ensure the temporal consistency of the analyses, since these were only compiled systematically after 1988 (Jiménez-Ruano et al., 2017b).

2.3. Identifying fire regime typologies by means of cluster analysis

2.3.1. Training clusters

The cornerstone of the analyses lies in the identification of homogenous groups of fire activity in the two analyzed periods. We applied cluster analysis, training clusters in the current period to later project them into the past. The rationale behind was to characterize current fire regimes and assess their evolution from the past as a necessary step to model the future distribution in the Jiménez-Ruano et al. ("Unpublished results"). Fire features were first submitted to Principal Component Analysis where components that met the Kaiser Criterion (Kaiser, 1960) were retained. Then optimized hierarchical clustering was applied to the selected principal components. The clustering strategy consisted of *Canberra* distance (Cd) and *ward.D2* agglomeration criteria (Sørensen, 1948). The optimal number of clusters was determined using the *nbClust* R package using to the highest ranked number of clusters out of the 30 indices available in the package (Charrad et al., 2014). The resulting clusters were considered representative fire regime typologies.

2.3.2. Projecting clusters into the past

The set of clusters obtained in the current period was "projected into the past" using k-nearest neighbor (KNN; Ripley, 1996) classification. KNN is a nonparametric classifier that finds the closest K neighbors (K=5) according to their similarity/dissimilarity measured as the distance in an N-dimensional space (where N equals the number of features characterizing each observation, i.e., N=5 fire features). The assigned class in KNN is the most frequently observed among the K neighbors. The regular version of KNN determines the distance between neighbors calculating the Euclidean distance. To be consistent with the clustering strategy, we used the knnVCN algorithm (Venables and Ripley, 2002), an alternative implementation of KNN able to measure dissimilarity using the *Cd*. Cd measures distance as the sum of the fraction of differences between the coordinates of a pair of observations (Teknomo, 2015). Terms with zero numerator and denominator are omitted from the sum and treated as missing values (Charrad et al., 2014). The equation of the Cd is as follows:

$$Cd\ (x, y) = \sum_{j=1}^{d} \frac{|xj - yj|}{|xj| + |yj|}$$

where *xj* is the first observation with coordinates of the features and *yj* is the second observation with its corresponding coordinates of the same features. Each term of fraction difference ranges from between 0 to1.

We used the current distribution of clusters and its corresponding values of fire features to reproduce their spatial distribution under past conditions, i.e. assign the most similar cluster to each grid cell in the past period. Given the critical importance of the proper identification of clusters, we evaluated the predictive performance of the KnnVCN approach, i.e., the capability of the method to transfer clusters according to the observed fire features. To that end, we randomly split the current set of clusters using a 70% of the grid cells for prediction and the remaining 30% to estimate the agreement in the classification calculating the Kappa Cohen's index (Cohen, 1960). In this process, we train clusters using 70% of the data and then, using the remaining 30%, we compare the 'observed' cluster assign from the initial classification, with the cluster 'predicted' applying KnnVCN. This provides a measure of the reliability of the transposing procedure. The process was repeated resampling the data pool 100 times to ensure the consistency of agreement measurements.

2.4. Modeling fire regime change

The main goal of this work was to identify the drivers of fire regime dynamics and its marginal influence in the evolution of fire activity. To this end, we trained random forest models relating the observed trajectories of fire regime change and drivers of wildfires.

2.4.1. Dependent variable

The dependent variable, change versus no change in fire regime (cluster type), was constructed from the combination of current and past cluster typologies at grid level. To do so, we constructed the transition matrix of cluster typologies between the past and current periods. It must be noted that not all combinations of change were assessed but only those more frequently observed. Thus, according to the transition matrix, we selected those combinations with at least 100 cells for each transition. Then, for each combination (further referred to as transition type), we built a separate response variable, classifying those cells where a change of fire regime was observed as 1 and those not changing as 0. For example, those grids where fire regime 1 was observed both in the past and current times are considered as '0' or no change whereas those that changed from fire regime 1 to 2 would be labelled as '1' or change.

2.4.2. Explanatory factors

Variables related to wildfire incidence and its temporal evolution were selected based on drivers commonly reported in the literature (Costafreda-Aumedes et al., 2017; Leone et al., 2003), granting special consideration to those already explored in Spain (Jiménez-Ruano et al., 2017b; Rodrigues et al., 2018, 2016).

Variables related to human pressure on wildlands (WUI; or the demographic potential) and the presence of agricultural activities or machinery close to forested areas (WAI), were expected to increase wildfires. However, those locations close to populated places may also be subject to increased suppression capability, and thus, smaller fires. In some cases, the presence of agricultural activities alters the duration and timing of the fire season with increased fires during late winter or early spring. In addition, climate-related variables (temperature and precipitation) mainly influence the fuel load and moisture content. Consequently, under hazardous conditions they hinder suppression, leading to potentially larger fires. Finally, we selected elevation and slope as indicators of the complexity of the terrain. The first also connects with fuel distribution (altitudinal belts), whereas slope affects both accessibility and fire spread potential. Steeper slopes impede the movement of ground fire-suppression squads and boosts propagation, thereby fostering larger fires.

Since we were dealing with a dynamic process (i.e., change in fire regime) we tried to integrate the temporal behavior of explanatory factors when suitable. In this sense, we built non-stationary indicators of demographic potential and climate factors. The remaining factors were considered static provided that (i) they did not change during the study period, as is the case of topographical variables or (ii) the performance of the model was higher when they were considered stationary, as happens with WUI and WAI. All variables were spatialized using the baseline geometry of the 10x10 km grid (Fig. A1 and Fig. A2, Appendix C). The following list presents the select drivers of fire regime change:

- **Wildland-Agricultural Interface - WAI (m)**: length of the boundary line between agricultural lands (CLC code 2) and forest areas (codes 3.1 and 3.2). Land use data were retrieved from Corine Land Cover 1990, thematic level 3.
- **Wildland-Urban Interface - WUI (m):** length of the boundary line between urban settlements (CLC code 1.1) and forest areas (codes 3.1 and 3.2). Land use data were retrieved from Corine Land Cover 1990, thematic level 3
- **Demographic potential - DP (dimensionless):** The demographic potential is an index reflecting the "demographic power" as well as the ability to provide population growth in the near future in terms of accessibility (Calvo and Pueyo, 2008). The calculation of DP is as follows:

$$DP_i = \sum_{j=1}^{n} \left(\frac{P_j}{dr_{ij}^2} \right) + P_i$$

where *Pj* is the population *P* at location *j*; *Pi* is the population *P* at location *i*; and *drij* is the distance by road between locations *i* and *j*. It was originally calculated at 5x5 km resolution and resampled to 10x10 km according to the average value. The demographic potential was expressed as the rate of change between 1991 and 2001, calculated as:

$$\Delta DP = \frac{DP_{2001} - DP_{1991}}{DP_{1991}}$$

- **Temperature – T (Cº):** average monthly temperature was retrieved from the MOTEDAS database (González-Hidalgo et al., 2015). MOTEDAS data were distributed in a 10x10 km grid; values were resampled according to the nearest neighbor cells. Temperature data were also converted into a dynamic trend indicator. We calculated the Sen's slope (Sen, 1968) of the maximum (daytime) temperature for the period 1974-2010 as indicator of trend magnitude.
- **Precipitation – P (mm):** average monthly precipitation was retrieved from the MOPREDAS database (González-Hidalgo et al., 2011). As for MOTEDAS, MOPREDAS data were distributed in a 10x10 km grid, resampled to our grid according to the nearest neighbor cells. Same as temperature, Sen's slope was calculated to account for temporal dynamics in rainfall in the period 1974-2010 as indicator of trend magnitude.
- **Elevation – Elev (m.a.s.l.):** meters above sea level. Altitude was retrieved from the GTOPO30 1 km Digital Elevation model (Earth Resources Observation and Science Center/U.S., 1997). It was resampled to the of 10x10 km grid as the average elevation of all pixels within a cell.
- **Slope – Slp (%):** percent of rise in elevation calculated from the altitude layer. Slope was calculated using the original 1 km resolution, being later resampled into grid cell size as the average slope of all pixels within a cell.

2.4.3. Random Forest modeling

The procedure to assess the role of the drivers in fire regime change was based on the calibration of probabilistic binary models, i.e., change vs no change. We selected the Random Forest (RF; Breiman, 2001) modeling algorithm given its proven predictive accuracy (Bar Massada et al., 2012; Leuenberger et al., 2018b; Rodrigues and de la Riva, 2014b). RF is a tree-based ensemble algorithm that trains multiple decision trees by randomly bootstrapping the training sample, keeping 67% of the observations to train the decision tree and the remaining 33% (Out-Of-Bag, OOB) to evaluate the relative influence of the predictors and the model itself. The final stage assembles all trees into a final prediction as the average of all individual tree predictions (*Bagging*; Breiman, 2001).

For each transition type, we trained and validated 100 RF models, using a random sample of 70% for training and the remaining 30% for testing the performance of the model. At the training stage, a 10-fold calibration procedure was conducted to identify the optimal parameters (*mtry* and *ntrees*) of the model. Also, during the training stage the influence of each driver was evaluated by calculating the percentage increase in the Mean Square Error (normalized between 0 and 1), and its explanatory sense by means of partial dependence plots (Jerome H Friedman, 2001). To estimate the predictive performance of each model realization the Area Under the Receiver Operating Characteristic Curve was calculated (AUC; Bradley, 1997). Additionally, the explanatory meaning of the covariates (either positively or negatively related) was explored by visual inspection of partial dependence plots.

3. RESULTS

3.1. Fire activity in the study region

According to fire statistics from the Spanish fire database, fire activity has experience a great decline from past to current conditions (Table 1). There has been a huge decrease in BA, two time lower in the current period (4,106,790 ha vs 1,998,304 ha). Likewise, BA100 and BAL also diminished towards nowadays. The decline is also patent in F, though moderate compared with BA. The only feature that has experienced an increase in figures is FW, augmenting from 31,598 to 50,167 fires burning during winter.

Table 1. Comparison of fire activity between current and past conditions. F: fire frequency, FW: number winter frequency, BA: burned area, BA100: burned area by large fires, and BAL: natural burned area.

	F	FW	BA (ha)	BA100 (ha)	BAL (ha)
Past	117,463	31,598	4,106,790	2,838,328	288,149
Current	111,605	50,167	1,998,304	1,185,599	110,645

3.2. Observed clusters and transitions

Fire features belonging to the current period were submitted to PCA as a preliminary step towards the cluster analysis. We retained the three first components, which gathered around 98% of the total variance. The first component (PC1, 58% of the variance) relates to intense human-caused fire incidence, correlating with all features apart from burned area from natural fires. The second (PC2, 25% variance) mostly correlated with BL and to some extent with BA100. Noticeably, the loadings of number of fires and winter fires were negative, thus suggesting PC2 related to rare, large and natural-caused fire events during summer. The third and last component (PC3, 15% variance), also correlated with natural fires but in this case smaller and most frequent events (negative correlation with BA100 and positive with F).

3.2.1. Fire regime typologies

Cluster analysis produced five fire regime types (Fig. 4 and Table 2). The KNN classification yielded a good agreement with an average accuracy of 93.3%. To facilitate the interpretation of the results, clusters were ranked from 1 to 5 according to their hazardousness. Overall, we considered that clusters leading to increased burned area or fire frequency, or pointing towards the increased of human influence as more dangerous and vice versa. Cluster 1 gathered areas with low fire activity. Cluster 2 grouped medium-sized wildfires with fair contribution of lightning-caused fires. Cluster 3 collected medium-sized fires, but with fair contribution of human-caused fires. Large fires with frequent lightning fires characterized cluster 4. The last cluster depicted the greatest fire incidence (fire frequency and burned area) and large fire occurrence, with a large fraction of winter fires.

Low-to-moderate fire activity typologies (clusters 1 and 2) were the most frequently observed (48.8% and 62.0 % of cells, past and current respectively). The spatial footprint of theses clusters extended over the hinterlands (Fig. 4), although towards the current period it has progressed towards the Mediterranean coast. Intermediate fire regime (cluster 3) was more frequent under current conditions (17.1%) than in the past (10.4%). Clusters showing the highest fire incidence (clusters 4 and 5) covered 20.9% of the fire-affected territory, decreasing from a 40.9% in the past. Fire regime 4 was observed both in the northwestern end and the Mediterranean coast in the past, being only observed in small enclaves in these same regions in the current period. Fire regime 5 was detected also in the northwest under past conditions and some sparse locations within the hinterlands. Nowadays, it is only observed along the northern coast, progressing from cluster 4.

Table 2. Summary of characteristics of fire regime typologies. F: fire frequency, FW: winter frequency, BA: burned area, BA100: large burned area, and BAL: natural burned area. Bold numbers indicate average values whereas median appear in italics.

					PAST		
Cluster ID	Cells	%	F	FW	BA	BA100	BAL
1	989	29.9	**0.02**-*0.01*	**0.00**-*0.00*	**0.28**-*0.09*	**0.08**-*0.00*	**0.00**-*0.00*
2	624	18.9	**0.04**-*0.04*	**0.01**-*0.00*	**1.45**-*1.27*	**1.06**-*0.87*	**0.09**-*0.01*
3	344	10.4	**0.07**-*0.06*	**0.03**-*0.02*	**0.68**-*0.47*	**0.04**-*0.00*	**0.02**-*0.00*
4	863	26.1	**0.24**-*0.15*	**0.05**-*0.03*	**14.09**-*9.61*	**11.16**-*6.96*	**1.26**-*0.01*
5	488	14.8	**0.37**-*0.20*	**0.12**-*0.06*	**5.94**-*2.71*	**2.17**-*0.44*	**0.03**-*0.00*
					CURRENT		
Cluster ID	Cells	%	F	FW	BA	BA100	BAL
1	1,657	50.1	**0.01**-*0.01*	**0.00**-*0.00*	**0.13**-*0.02*	**0.03**-*0.00*	**0.00**-*0.00*
2	393	11.9	**0.04**-*0.03*	**0.01**-*0.00*	**1.18**-*1.00*	**0.87**-*0.69*	**0.12**-*0.01*
3	566	17.1	**0.08**-*0.06*	**0.03**-*0.02*	**0.50**-*0.35*	**0.04**-*0.00*	**0.01**-*0.00*
4	322	9.7	**0.23**-*0.12*	**0.09**-*0.04*	**12.05**-*6.9*	**9.93**-*5.58*	**1.12**-*0.03*
5	370	11.2	**0.78**-*0.55*	**0.40**-*0.23*	**8.37**-*6.03*	**2.98**-*1.43*	**0.06**-*0.00*

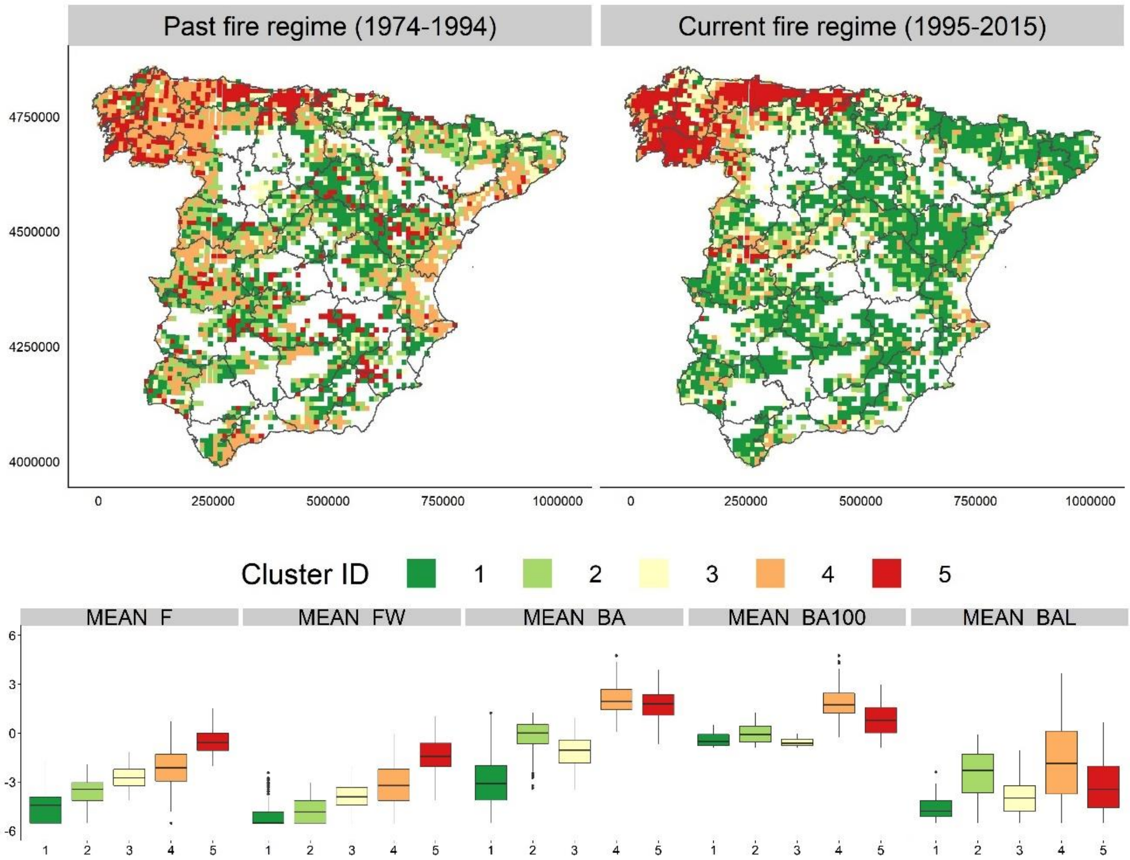

Fig. 4. Top: spatial distribution of clusters in the two periods. Bottom: distribution of current fire features per cluster (values were log-transformed to enhance visualization). F: number of fires; FW: number of fires during autumn-winter season; BA: overall burned area; BA100: burned area from large fires (>100 ha), and BAL: burned area from natural-caused fires.

3.2.2. Fire regime transitions

Fig. 5 and Table 3 summarize the most frequent fire regime transitions (CT) and their spatial distribution. Our findings revealed that lower fire activity (type 1) progressed across the hinterlands towards the Mediterranean (959 cells out of 3,308). Medium-sized fires associated with lightning fires (type 2) were confined to the hinterlands in the past. Although its spatial extent shrank over time, this regime shifted towards the Mediterranean coast over time (119 cells). Intermediate fire regime (type 3) dominated the northeastern façade along the Pyrenees in the past. Currently, this typology of fire regime progressed from higher order types (4 and 5) across the territory, especially in the northwestern end and the Mediterranean coast. However, the sparse enclaves of type 3 within the hinterlands have usually transitioned from lower activity (type 1 and type 2) in the past. Large and natural fires (type 4) were most frequent in the past, covering vast regions in the Northwest, the western half of the hinterlands and most of the Mediterranean coast. However, their extent has greatly declined towards present, mostly replaced by low activity. Finally, regimes associated with large incidence of fires in fall-winter (type 5) was scatter over small clusters in the northwestern region, the hinterlands and a small enclave in the Mediterranean. However, it only persists in the northern coast, reaching a vast and continuous coverage in the current period.

In general, the decline in fire activity was the most common pathway over time (2-1: 364 cells past-current, but also 4-1: 242 cells), perhaps being stronger in the Mediterranean area. Nonetheless, we have found some CTs exhibiting a major increase in fire activity (dark orange cells from Table 3), we consider them non-significant due to their low number of cells (less than 40). Finally, the most stable typologies were the 1 and 4 (698 and 200 cells, respectively). These fire regimes more persistent are located mainly in the Northwest region and scattered over numerous mountainous areas of the hinterland (Fig. 5 - top).

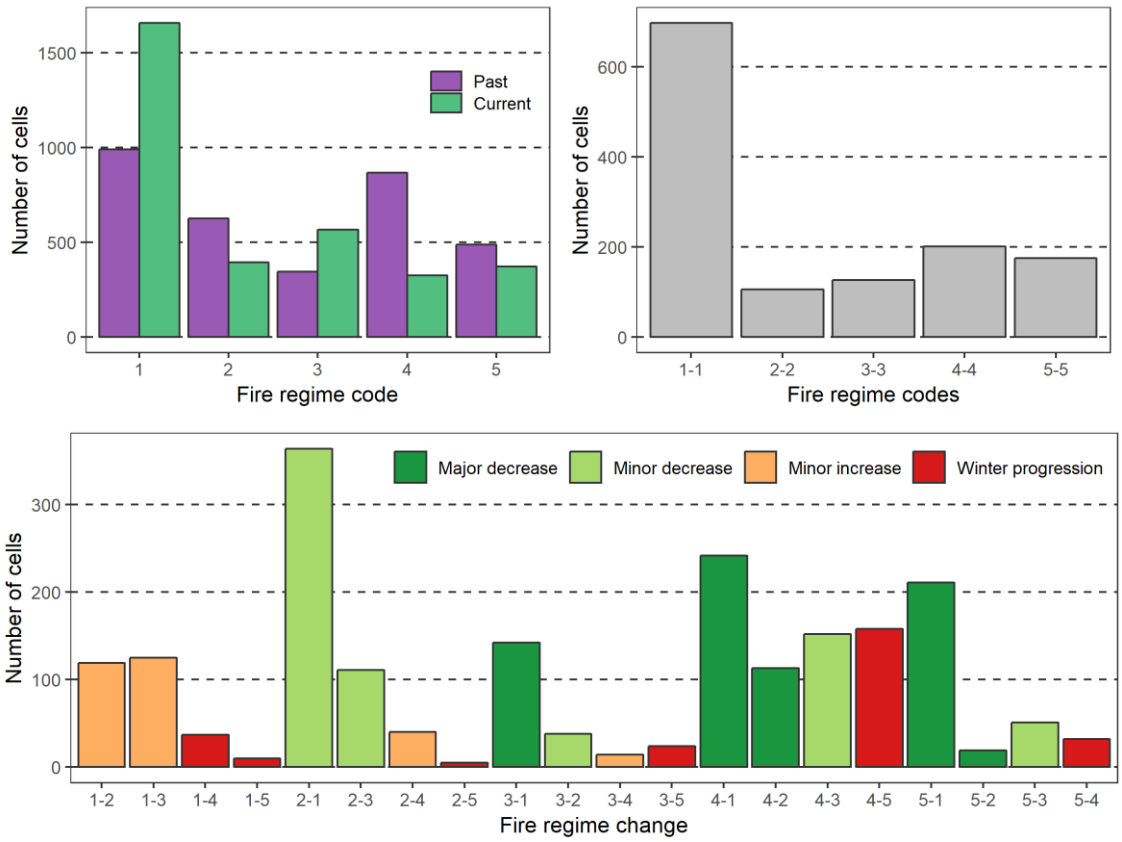

Fig. 5. Frequency histograms (number of cells) of current and past fire regimes (top-left), stable trajectories (top-right), and transitions (bottom).

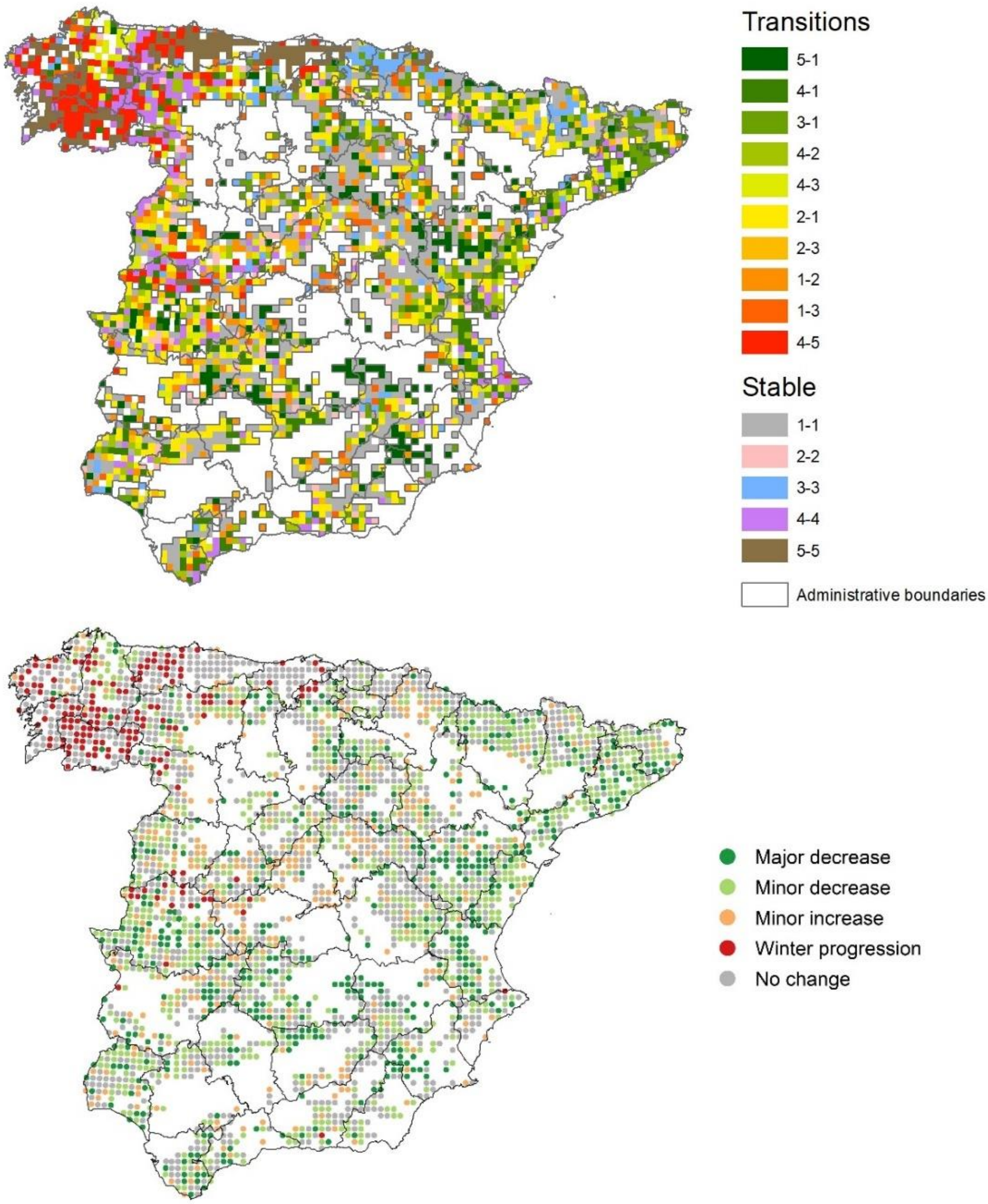

Fig. 6. Top: fire regime transitions between past and current conditions. Bottom: summary of main trajectories across the study region.

Table 3. Transition matrix between past-current clusters. The most frequent CT were highlighted in bold. In color each degree of CT (major decrease: dark green, minor decrease: light green, minor increase: orange, winter progression: red). The grey cells correspond to the non-change of clusters. Bold indicates those trajectories evaluated by RF modeling.

		Current					
		1	2	3	4	5	Total
Past	1	698 (70.6%)	**119 (12%)**	**125 (12.6%)**	37 (3.7%)	10 (1.0%)	989 (100%)
	2	**364 (58.3%)**	105 (16.8%)	**111 (17.8%)**	39 (6.3%)	5 (0.8%)	624 (100%)
	3	**142 (41.3%)**	38 (11.0%)	127 (36.9%)	14 (4.1%)	23 (6.7%)	344 (100%)
	4	**242 (28%)**	**112 (12.9%)**	**152 (17.6%)**	200 (23.2%)	**157 (18.2%)**	863 (100%)
	5	**211 (43.2%)**	**19 (3.9%)**	51 (10.5%)	32 (6.5%)	175 (35.9%)	488 (100%)
	Total	1657 (50.1%)	393 (11.8%)	566 (17.1%)	322 (9.7%)	370 (11.2%)	3308 (100%)

3.3. Drivers of fire regime transition

Random Forest modeling provided insights into the overall contribution of wildfire drivers (Table 4). In general, the performance of the models was satisfactory, yielding AUCs above 0.70 in most of the transitions investigated. The change from large to low fire activity (5-1 and 4-1, Fig. B10 and Fig. B6 in Appendix C) attained the highest AUC (0.96 and 0.90, respectively). On the contrary, we obtained modest performances in those transitions depicting increased fire incidence (1-2: 0.59 and 2-3: 0.60).

The change in the Demographic Potential (DP) was often found as the most influencing factor, displaying strong positive relationships in declining trajectories, though its contribution weakens in progressive pathways. For instance, DP portrayed a 'v-shaped' curve in trajectories 1-3 and 1-2 (Fig. B1 and Fig. B2 – Appendix C), corresponding to minor increments in fire incidence. Nonetheless, the increase in DP was linked with regressive trajectories. Conversely, an inverse relationship was observed in the progression from large fire activity during summer towards fall-winter. Thus, the incidence of wildfires in locations with increased human presence declined whereas the loss of DP promoted human-related fires during winter. Second in importance, we found trends in annual precipitation (P). Overall, increasing trends in P match declining fire incidence, and decreasing P led to increments in fire activity. There were however some exceptions to this behavior. For instance, the transition from low incidence to medium-sized natural fires was promoted by increasing trends in precipitation (Fig. B1 in Appendix C). In turn, slope consistently showed inverse relationships, regardless of the kind of trajectory. For instance, it promoted the change from winter and human dominated fire regimes to low activity, which took place mostly in the plains within the hinterlands or along the Mediterranean coast, only persisting in the northern coast, which is characterized by complex topography. On the other hand, it influenced progressive trajectories characterized by medium size fires strongly related to human activities (1-3 and 2-3, Fig. B2 and Fig. B4, Appendix C). The response to elevation is rather straightforward, the higher the altitude the lower the fire incidence and vice versa. Transitions leading to increased fire activity (1-3 and 2-3) were clearly related to the presence of WUI. Conversely, inverse relationships were observed either in trajectories linked to increased fires during fall-winter (4-5, Fig. B9 Appendix C) or showing a decline in fire activity (2-1 and 4-3, Fig. B3 and Fig. B8, Appendix C). Finally, increased WAI boundary promoted the increase in winter fire frequency.

Table 4. Red values =direct relationship; blue = inverse relationship; purple = v–like curve. Grey-shadowed means no clear explanatory sense. Dark green indicates major decrease in fire activity, light green minor decrease, Dark red major increase and orange minor increase.

Transition	DP	Elev	Slp	T	P	WAI	WUI	AUC	Description
4-1	100	0	11	45	10	6	30	0.90	From high to low
5-1	100	25	71	30	70	5	0	0.96	From high with winter to low
4-2	100	5	25	10	2	0	0	0.71	From high to medium with lightning
3-1	75	55	10	50	100	70	0	0.78	From medium to low
4-3	65	0	100	80	71	25	40	0.64	From high to medium
2-1	100	24	12	15	20	0	50	0.65	From medium with lightning to low
4-5	50	15	0	25	74	100	50	0.76	From high to high with winter
2-3	50	60	60	20	40	0	100	0.60	Medium with lightning to human
1-3	80	70	100	0	70	20	65	0.72	From low to human
1-2	70	100	24	40	65	26	0	0.59	From low to medium with lightning
Average	79.0	35.4	41.3	31.5	52.2	25.2	33.5	0.73	

4. DISCUSSION

In this work, we presented and applied a methodology to identify and spatialize fire regime typologies that enabled further insights into the underlying drivers of its spatial-temporal dynamics. To the best of our knowledge, this was the first attempt to incorporate the temporal perspective into fire regime zoning in Spain, complementing the findings by Curt and Frejaville (2017) in southern France. The main novelty of our proposal lies not only in applying the zoning scheme in two historical periods but in completing them with regression models, deepening into the traits behind the spatial-temporal behavior of fire regime.

Cluster analysis revealed five fire regime typologies. (1) low fire activity, (2) medium-sized wildfires with fair contribution of natural-cause, (3) medium-sized forest fires with a high weight of human-caused fires, (4) large wildfires with a remarkable presence of lightning, and (5) the high fire incidence with noticeably winter activity. The suggested fire regime delimitation (Fig. 4) resembled that from previous work in the same region (Moreno and Chuvieco, 2013). Although conceptually the approaches were similar, ours distinguished five fire regime typologies (instead of 4) and required fewer fire features.

These fire regime typologies were successfully transferred into the past using KNN classification (Kappa ≈ 0.9), ensuring the reliability of the observed changes in fire regime. In line with previous studies about trends in fire activity, the most common pathway led to decreased fire activity, especially along the Mediterranean coast (Jiménez-Ruano et al., 2017; Rodrigues et al., 2013; Silva et al., 2019). In some enclaves within the hinterlands and, most of all, in the northwestern end, the observed dynamics pointed towards the "humanization" of fire regime while keeping the impact of fires in terms of burned area and fire size (Fig. 5).

According to RF models, the change in DP appeared to be the strongest feature behind fire regime dynamics, being positively related with higher likelihood of change in all decreasing transitions (Table 4). Thus, increased DP diminished fire incidence. As population grows so does fire incidence (Costafreda-Aumedes et al., 2017b). However, the aforementioned relationship is not necessarily true in those regions under a total fire exclusion policy (Silva et al., 2019) and, paradoxically, there is a tipping point in population density (Fig. B3, Fig. B6 and Fig. B7 in Appendix C) from which likelihood of large fires declines (Syphard et al., 2009). Indeed, human beings foster fire occurrence but under milder temperature and low wind speed conditions most fires are controlled and extinguished during the initial attack (Duane and Brotons, 2018; Rodrigues et al., 2019a). However, increased human pressure in the WUI has been observed to foster human-related fire progression (Fig. B2 Appendix C) in the surroundings of Madrid and Central System Range (Romero-Calcerrada et al., 2008; Vilar del Hoyo et al., 2008). Contrary to the DP, which depicts overall trends in population and accessibility, the WUI comprises residential settlements in contact with forestlands. WUI may act both as a source of fire ignitions and as an accessibility corridor for firefighting brigades enhancing fire containment (Leone et al., 2003b). This may explain the moderate increase in fire activity but modest size of the resulting fires. Of course, we are talking in terms of average values and trends and, evidently, large fires still happen. Noteworthy, the loss in DP in confluence with WAI boundaries, decreased rain and no WUI explained the progression of winter fires (Table 4). We considered the increment of fire incidence outside the main wildfire season (4-5) as the most hazardous trajectory, since it implies the shift towards human-related fire activity and an extended wildfire season. Weather conditions during fall-winter are unfavorable to fire incidence, but under persistent drought events, fires can still occur and become uncontrolled (Bedia et al., 2014). We found evidence of this in the extraordinary large fire events during 2017 when 68% of large fires (>500 ha) started during winter (ADCIF, 2017). This peak in forest fires in the winter season is closely related to both intentional and accidental fires linked to agricultural activities (Moreno et al., 2014; Prestemon et al., 2012; Rodrigues et al., 2018).

Climate trends showed contrasted relationships. From a geographical point of view, the decreasing transitions of fire incidence experiencing a rise in temperature are widespread in the hinterlands and along the Mediterranean coast, supporting the observed disconnection between fire weather danger and fire incidence due to fire suppression (Jiménez-Ruano et al., 2019). On the other hand, the transitions of increased weather hazardousness overlapped the mountainous areas in the northern plateau, which showed growing fire activity due to intensified fire prone conditions in densely vegetated areas (Castedo-Dorado et al., 2011; Vázquez and Moreno, 1998). In turn, the increase in precipitation connected with downward trends in fire activity. Abundant rainfall means higher fuel moisture content which ultimately constrains the spread of wildfires (Argañaraz et al., 2018). By contrast, inverse associations, i.e. decreasing trends in precipitation matched both winter progression and minor raise in fire incidence in the northwest (de Luis et al., 2010; Paredes et al., 2006). Finally, elevation and slope displayed a negative link with fire activity, thus low and flat lands experienced increased fire incidence (González and Pukkala, 2007; Viedma et al., 2018). In fact, this pattern matched the distribution of urban settlements in Spain, which proliferated in coastal zones and lowlands preferably.

From a managerial and policymaking perspective, our findings may provide valuable guidance and recommendations. For instance, those regions where a drastic decrease in fire activity was observed (transitions from types 4 and 5 to 1) are more likely to experience a gradual increase in fuel loads and continuity. Likewise, cropland abandonment and the decline of extensive livestock envisage larger fires in the future (Pausas and Paula, 2012). To some extent, the current suppression policy seems to be counterbalancing this effect but it might become override under an scenario of increased fire weather danger exceeding the suppression capacity (Fernandes et al., 2014; Jolly et al., 2015; Turco et al., 2018). On the other hand, the advance in fire activity in some locations highlights the necessity of improving fire management. For example, more attention must be paid to the autumn-winter wildfire season in forthcoming years, to a point of even redefining the timing of the fire seasons as suggested by Costafreda-Aumedes et al. (2018). In summary, the role played by the driving factors is strongly valuable for forest fire planning and management, and should be used to help budget allocation and contribute to the design of extinction and prevention plans (i.e., prescribed burning, fuel cleansing...).

5. CONCLUSIONS

In this work, we proposed the first attempt to outline fire regime regions incorporating a temporal perspective in Spain. We explored historical past (1974-1994) and current (1995-2015) fire activity (retaining only the fires burning more than 1 hectare), engaging zoning schemes with exploratory regression analysis.

We identified and characterized five fire regime typologies depicting (1) low fire activity, (2) medium-sized wildfires with fair contribution of natural-cause, (3) medium-sized forest fires with a high weight of human-caused fires, (4) large wildfires with a remarkable presence of lightning, and (5) the high fire incidence with noticeably winter activity. These five typologies were spatialized in the two aforementioned periods to ascertain the most frequent trajectories of fire regime change. Overall, declining transitions (i.e., conducive to lower fire activity) were the most common pathways, covering a remarkable extension. However, fire regimes associated with winter activity have advanced in the Northwest and persisted along the northern coast.

Our results revealed the link between drivers of wildfire and the observed dynamics. Demographic potential appears as the main factor involved in most transitions, followed by climate trends. The wildland interfaces (WAI and WUI) displayed a direct association with increasing transitions (including winter progression) and inverse in the declining ones.
Finally, from a managerial perspective, our findings may help to identify regions that may experience fuel accumulation, targeting them as priority interventions areas to decrease the chances of large fires in the coming years.

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Declaration of Competing Interest

The authors have no conflicts of interest to declare.

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Fire regime dynamics in mainland Spain. Part 2: a near-future prospective of fire activity

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Abstract
The current research belongs to a series of two manuscripts aiming at describing spatial-temporal dynamics of fire regime and its drivers in Spain. In this work, we present the first attempt to produce a spatial-temporal delimitation of homogeneous fire regime zones in Spain providing insights into the near future. The analyses were based on historical fire records; leveraging autoregressive ARIMA models to project fire features into the near future. We evaluated the spatial extent of homogenous fire regime zones in three different periods: past (1974-1994), current (1995-2015) and future (2016-2036). To do so, we applied Principal Component Analysis (PCA) and Ward's hierarchical clustering to identify zones of fire regime on the basis of the spatial and temporal arrangement of their main fire features: number of fires, burned area, burnt area from natural-caused fires, incidence of large fires (> 100 ha) and seasonality. Clusters of fire regime were trained in the current period, being later projected into the past and future periods using of k-Nearest Neighbor classification.

ARIMA modeling forecasted a shrinkage in all fire features except natural-caused fires that remained stable. Overall, we detected a transition from significant fire incidence in the past towards a situation with moderate impact of fires in the near future. The Mediterranean coast experienced the largest decline in fire activity with few locations maintaining the historical levels of occurrence of large fires. On the other hand, the Northwestern end of Spain depicted a progression towards winter fire activity while still linked to large fires. This pattern persisted in the near future along the northern coast, whereas an intermix of minor fire progression and regression was expected thorough the hinterlands and the Mediterranean.

Keywords: Forest fires, fire regime, fire features, ARIMA, future projection, suppression policy

1. INTRODUCTION

Forest fire management and prevention have gained attention over the years, being currently under the spotlight due to the uncertain effects of climate and socioeconomic changes. Expenditures in fire suppression and prevention are increasing globally, especially in fire-prone developed countries where a total fire exclusion policy is often implemented (Stephens et al., 2014). For instance, the US Federal Land Management bureau spent more than 2 billion $ in fire management during 2015 (Doerr and Santin, 2016). The annual budget in firefighting in the European Union raises to approximately 2.2 billion € (Faivre et al., 2018). In the case of Spain, one of the most fire affected countries within the European Mediterranean region currently ranking second in fire incidence only after Portugal (San-Miguel-Ayanz et al., 2017), fire suppression and prevention have been increasingly funded up to circa 78 million € in 2015 (MAPAMA, 2017). Therefore, it seems clear that firefighting agencies envisage a worsening fire danger scenario in the future, with more hazardous weather conditions increasingly threating human and environmental assets (Alcasena et al., 2019; Badia et al., 2011). For instance, fire incidence seems to be increasing in the Scandinavian countries. In 2018 this region experienced the warmest fire season within the recording period, which undoubtedly contributed to boost fire spread and overcome the extinction capacity (Martin Ruiz de Gordejuela and Puglisi, 2018). However, outside these exceptional cases, the current situation in those regions and countries historically affected by recurrent fires tells otherwise. In the Mediterranean Europe the observed number of fires and burned area is decreasing (Turco et al., 2016). At the same time, a remarkable decline in global fire-related emissions since 1930s is reported reaching the minimum in 2013 (Arora and Melton, 2018; Van Der Werf et al., 2017). One of the main reasons behind this trend relates to the fire exclusion policy, i.e., suppressing all wildfires in a region (Smith, 2000). Such policy considers wildfires as a negative hazard and consequently they must be suppressed by all means. Notwithstanding some authors believe the persistence of such policy will lead to increased large fire activity in the long-run due to substantial fuel accumulation (the so-called 'fire paradox', Otero and Nielsen 2017; Regos et al., 2014; Westerling, 2016) in conjunction with drier and warmer conditions (Chaparro et al., 2016; Ruffault et al., 2017; Turco et al., 2017). At the same time, questions about its sustainability are starting to raise (Curt and Frejaville, 2018).

Projections of fire incidence into the future have been extensively addressed in the literature. They were usually conducted according to climate change scenarios mostly based on General Circulation Models (GCM) coupled to IPCC's emissions scenarios or Regional Climate Models (RCM). Conversely to the observed trend (overall decrease in fire incidence) most works leveraging climate models envisage increased fire activity through the XXI century. Without being exhaustive, an increment in burnt area was reported in Portugal (DaCamara et al., 2014), Canada (Hope et al., 2016), California (Westerling et al., 2011) or the Iberian Peninsula (Sousa et al., 2015); gross fire activity was expected to augment in Canada (Boulanger et al., 2013; Wang et al., 2015), Northeast China (Liu et al., 2012), Finland (Kilpeläinen et al., 2010). Similarly, some works foresee a global (Liu et al., 2010) or regional (Jolly et al., 2015; Moriondo et al., 2006; Wotton et al., 2017) raise in fire weather danger. Some studies point out diverse tendencies depending on the global regions (Krawchuk et al., 2009; Pechony and Shindell, 2010), or even opposite trends with increasing frequency and a stability or slight decrease in burnt area in the Northeast of Spain (Turco et al., 2014). Although the goal of this work is not criticize climate-based approaches, they mainly address long-term trends while often disregard suppression efforts in their prediction. Moreover, several authors have pointed out the bias found between GCM's simulations and observations (Maraun, 2012). Differences in precipitation and surface temperature between the present and future climates indicate that present-climate biases are systematically propagated into future-climate projections at regional scales (Liang et al., 2008). In the particular case of Spain, the correlation between fire weather danger and fire incidence has been found to be rather weak, with weather controlling the seasonal patterns but exerting limited influence in the observed trends (Jiménez-Ruano et al., 2019). In this sense, suppression-related features such as the time elapsed until fire brigades reach the fire site or the scattering of suppression media during simultaneous fire events control the success of the initial attack whereas fire weather relates to sporadic large fire events (Connor et al., 2017; Duane and Brotons, 2018; Rodrigues et al., 2019a). Accordingly, we propose decoupling the temporal behavior of fire activity from other covariates (either climate or human related) to explore the near future evolution of wildfire features under the premise that their temporal behavior already integrates the influence of their underlying drivers. By doing so, we assume that weather conditions and human influence in wildfire activity would remain 'stable', i.e., they follow the same evolving trajectory and exert the same influence observed from past to current conditions as described in (Rodrigues et al., "Unpublished results", further referred to as 'Part 1').

Among the few modeling techniques that allow to forecast time series of data, the most well-known and widespread are the Auto-Regressive Integrated Moving Average (ARIMA) models. ARIMA only requires a univariate time series to forecast its future evolution, although versions that are more sophisticated allow incorporating additional covariates. ARIMA models are best known for its performance in economics and marketing (Loi and Ng, 2018; Matyjaszek et al., 2019), but also, environmental studies, such as vegetation dynamics (Jiang et al., 2010) or climate change (Afrifa-Yamoah, 2015). There are also experiences of ARIMA modeling in wildfire science. In North-America, Preisler and Westerling (2007) employed ARIMA to forecast temperature 1-month ahead to evaluate fire danger whereas Miller and Safford (2012) explored trends in large high severity fires. In Spain, Boubeta et al. (2016) applied ARMA (ARIMA without the integrated component) to predict weekly burnt area in Galicia. However, to the best of our knowledge there was no experience assessing the mid-to-long term evolution of fire regime features using ARIMA or any other autoregressive technique, at least in Spain.

In this work, we developed and exemplified a framework to identify and outline fire regime regions over time. The proposed approach included for the first time a near-future prospective based on the ongoing evolution of fire regime features. In the case of Spain, fire regime zoning experiences are scarce, finding some examples in Jiménez-Ruano et al. (2018), Montiel Molina and Galiana-Martín (2016) and Moreno and Chuvieco (2013). Nevertheless, these works provide a stationary picture of fire regimes without taking into account their temporal evolution. But fire incidence is non-stationary (Jiménez-Ruano et al., 2017a; Silva et al., 2019), a feature that encourages embracing a temporal perspective in fire regime assessments. Our core methodology allowed to identify homogenous fire regime zones in three different time periods. Past (1974-1994) and current (1995-2015) situations were addressed using historical fire records from the Spanish fire database. A third period was set in the near-future (2016-2036) forecasted by means of ARIMA extending from the current period. We hypothesized that the immediate evolution of fire regime would follow the ongoing pathway, thus assuming that climatic and human drivers of fire activity (both related to ignition and suppression) remain stable towards the near future. Our main goals were to a) outline current and past fire regime zones, b) forecast their immediate future evolution and c) describe the most representative spatial and temporal trajectories of fire regimes to (e) evaluate the disruptive effects of the current fire suppression policy.

2. DATA AND METHODS

The proposed methodology was sequenced in three stages. First, we retrieved historical fire records in the period 1974-2015 and organized them in two separate datasets (1974-1994 and 1995-2015). Then, we forecasted the evolution of fire incidence in the near future (2016-2036) using ARIMA models. Finally, we identified fire regime typologies in the current period (1995-2015) by means of cluster analysis and projected them into the past (1974-1994) and near future (2016-2036) using K-Nearest Neighbor (KNN) classification (see Fig. 1). All statistical procedures and plots were developed using the R statistical programming language (R Core Team and R Development Team Core, 2017), packages *forecast* and *stats* for future predictions, *NbClust* for cluster analysis, *knnGarden* for past and future cluster assignation, *splitstackshape* for KNN validation and *ggplot2* for mapping and plotting. Mapping was conducted using both R (*ggplot2*) and ArcGIS Desktop 10.6.

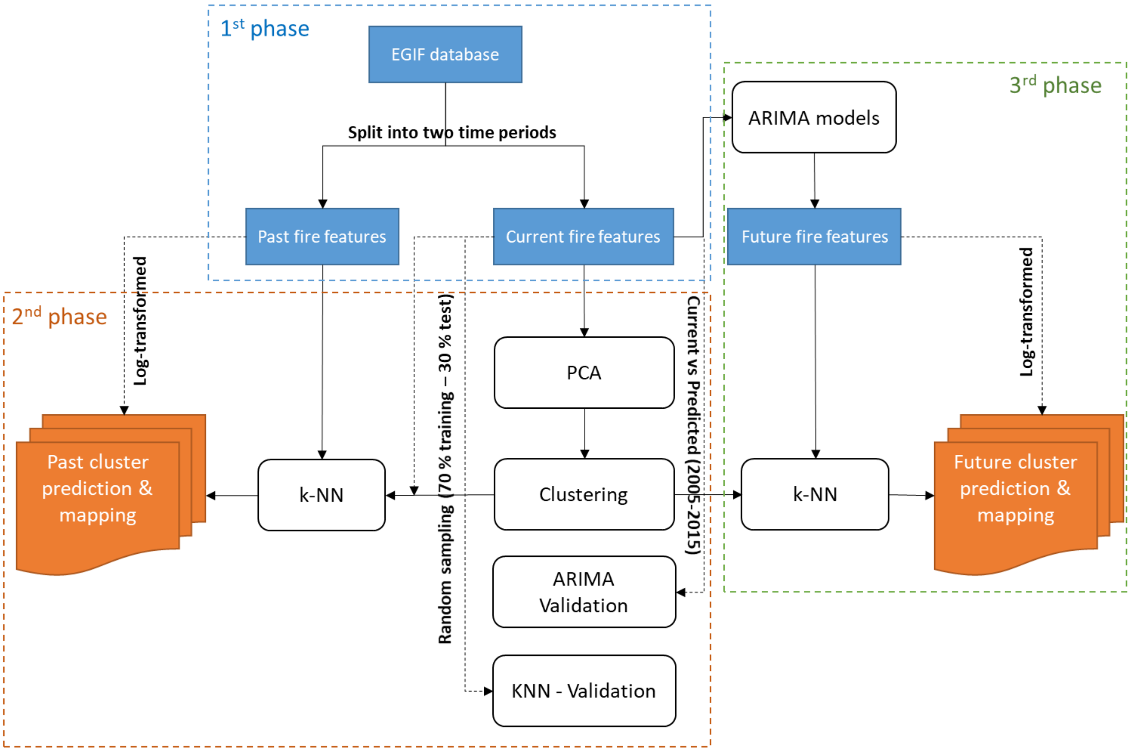

Fig. 1. General workflow of the methodology including input data split, clustering, KNN classification-validation and ARIMA validation from current to past and future fire features.

2.1. *Study area*

The region under study was mainland Spain. The region is mostly dominated by Mediterranean climate, with Oceanic conditions covering the northern end. Mediterranean climate was characterized by high annual thermal amplitude with hot summer in the inner region and milder conditions along the coast. Precipitation distributed irregularly over time and space, with maximums in autumn and spring, and minimum during summer months. The driest areas are located in the southeast region and the Ebro Valley. On the other hand, Oceanic climate distinguishes by milder temperature all over the year and high precipitation regularly distributed throughout the year (average values over 1,000 mm) peaking during winter. In terms of fire occurrence, the relevance of winter fires is really notable (35.7%), especially in the Northwest region. In turn, burned area by lightning represents a low fraction of total amount (around 6.5%) and it is usually concentrated in some mountainous areas. The surface affected by large fires (above 100 ha) accounts for 66% of the overall burned area. Comparatively, Spain ranks second in fire frequency (excluding small, i.e., fires < 1ha) among the most fire-prone countries in Mediterranean Europe (Table 1), after Portugal and before Italy, France and Greece. In the case of total burnt area, Spain stands out as the most fire affected, followed by Italy and Portugal.

Table 1. Number of fires and burned area (excluding fires <1 ha) per fire feature in mainland Spain for the period 1980-2016.Source: European Forest Fire Information System.

	Portugal	Spain	France	Italy	Greece
Burned area	3,973,670	5,991,140	912,309	3,899,998	1,661,816
Yearly burned area	107,396	161,923	24,657	105,405	44,914
Number of fires	669,698	547,135	174,462	337,722	53,983
Yearly number of fires	18,100	14,787	4,715	9,128	1,459

2.2. Fire data

Fire data was collected and organized following the procedure described in Part 1. However, we set a coarser grid of 30x30 km as spatial unit of analysis to warrant the 'stability' of future estimations via ARIMA models (by holding a larger pool of observations within each cell). Therefore, data from 10x10 km grids cells was aggregated into 30x30 km resolution as the sum of fire features, leading to a final set of 545 grids. As in Part 1, we built five fire features to further explore fire regimes distribution and evolution.

- **Fire frequency (F):** total number of wildfires per grid, month and period.
- **Burned area (BA):** total surface burned in hectares of the grid, month and period.
- **Burned area by nature cause (BAL):** surface burned by lightning in the grid, month and period.
- **Burned area by large fires (BA100):** burned area by fires greater than 100 hectares by the grid, month and period.
- **Winter frequency (FW):** number of wildfires occurred during autumn-winter (from October to March) by the grid, month and period.

2.3. Forecasting future fire regime features

As step further from Part 1, we applied auto-regressive models to forecast fire features into the near future. The targeted period was set at 2016-2036, extending twenty years beyond the historical period. This prospection assumes a continuant scenario in which the drivers controlling fire activity keep evolving following the same pathway observed between past and current conditions. The working premise was that drivers of fire activity are implicitly integrated in fire features and, thus they are a reflection the drivers themselves. To this end, we used ARIMA, a set of auto-regressive, integrated and moving average models for time series analysis. The use if ARIMA results advantageous to achieve our goal since it allows adjusting and forecasting models from univariate time series of a response variable, i.e., each fire feature. ARIMA models can be understood as a 'filter' that separates the signal from the noise, extrapolating only the signal into the future. ARIMA models can be only applied to stationary time series, i.e. with constant in mean and variance over time. In this work we submitted monthly time series of the aforementioned fire regime features in the period 1995-2015 to forecast their temporal evolution into the near future. Since fire features were known to be non-stationary (Jiménez-Ruano et al., 2017a) they were transformed using their square root forecasting purposes, and de-transformed afterwards to return to the original scale before being submitted to cluster analysis.

The ARIMA model provided several outputs, the most important of which was the mean forecasted value. Complementarily, ARIMA calculates two confidence intervals (80% and 95%), allowing setting upper and lower limits in the prediction. As reported by Hyndman and Khandakar (2008), the mathematical expression of the ARIMA formula is established as follows:

$$\Phi(B^m)\emptyset(B)(1-B^m)^D(1-B)^d y_t = c + \Theta(B^m)\theta(B)\varepsilon_t$$

where $\Phi(z)$ and $\Theta(z)$ are polynomials of orders P and Q respectively, each containing no roots inside the unit circle. If $c \neq 0$, there is an implied polynomial of order $d + D$ in the forecast function. The main task in automatic ARIMA forecasting is selecting an appropriate model order, that is the values p, q, P, Q, D, d. When d and D are known, the rest of orders are chosen by minimizing the Akaike Information Criterion (AIC; Akaike, 1974).

Finally, we evaluated the performance of the ARIMA prediction. We calculated the Pearson's R2 between ARIMA mean estimations (using data from 1974 to 2004) versus historical observations during the last 10 years of available fire reports (2005-2015). The analysis was applied comparing average values on the original 10x10 km grid and in the 30x30 km grid, to ascertain the effect of the spatial unit size, which ultimately justifies the use of the coarser 30x20 km grid.

2.4. Modeling clusters of current fire regimes

In order to identify fire regime typologies and zones, we applied cluster analysis, training clusters in the current period to later project them into the past and near future. We followed the procedure described in Part 1, but replicated to the 30x30 km grid. Principal Component Analysis and hierarchical clustering were applied to obtain fire regime typologies whereas KNN classification was used to project fire regimes into past and future periods. Finally, we identified the most frequent cluster transitions (CT) building two specific transition matrixes, one from past-current and another from current-future progressions. Additionally, we mapped the spatial distribution of cluster change (either towards the future or from the past), displaying CT categories and calculating the Canberra distance between the cell of origin (current) and the center of the destination cluster in order to illustrate the magnitude of the change.

3. RESULTS

3.1. Evolution of the fire regime features

Taking the historical period as baseline, future fire features showed a general decrease in their total values (Fig. 2). According to, Pearson's R2 coefficient between forecasted and observed fire features (Fig. 3), ARIMA predictions were reliable, capturing at least the 46% of variance (fire frequency) up to 76% in burned area. The coefficient of determination was consistently higher in the 30x30, compared to the original 10x10 grid.

The overall decreasing trend in fire activity was also observed in the spatial disaggregation of fire features (Fig. 4). At first glance, the spatial coverage of the highest interval in the past was greater than any other period. In fact, the temporal evolution showed a gradual decrease in all features, more noticeably in those related to burnt area (BA, BAL and BA100) that in the ones expressed as counts (F and FW). The spatial pattern of the future fire features largely matches the past and current, except in BAL and BA100, where values were generally lower and scattered across sparse grids over the territory. The highest activity concentrates in the Northern region, which in turn, was the most stable. The most pronounced decline in all fire features was observed along the Mediterranean coast. One of the most striking finding was the persistence of winter fire counts along the northern coast in the near future.

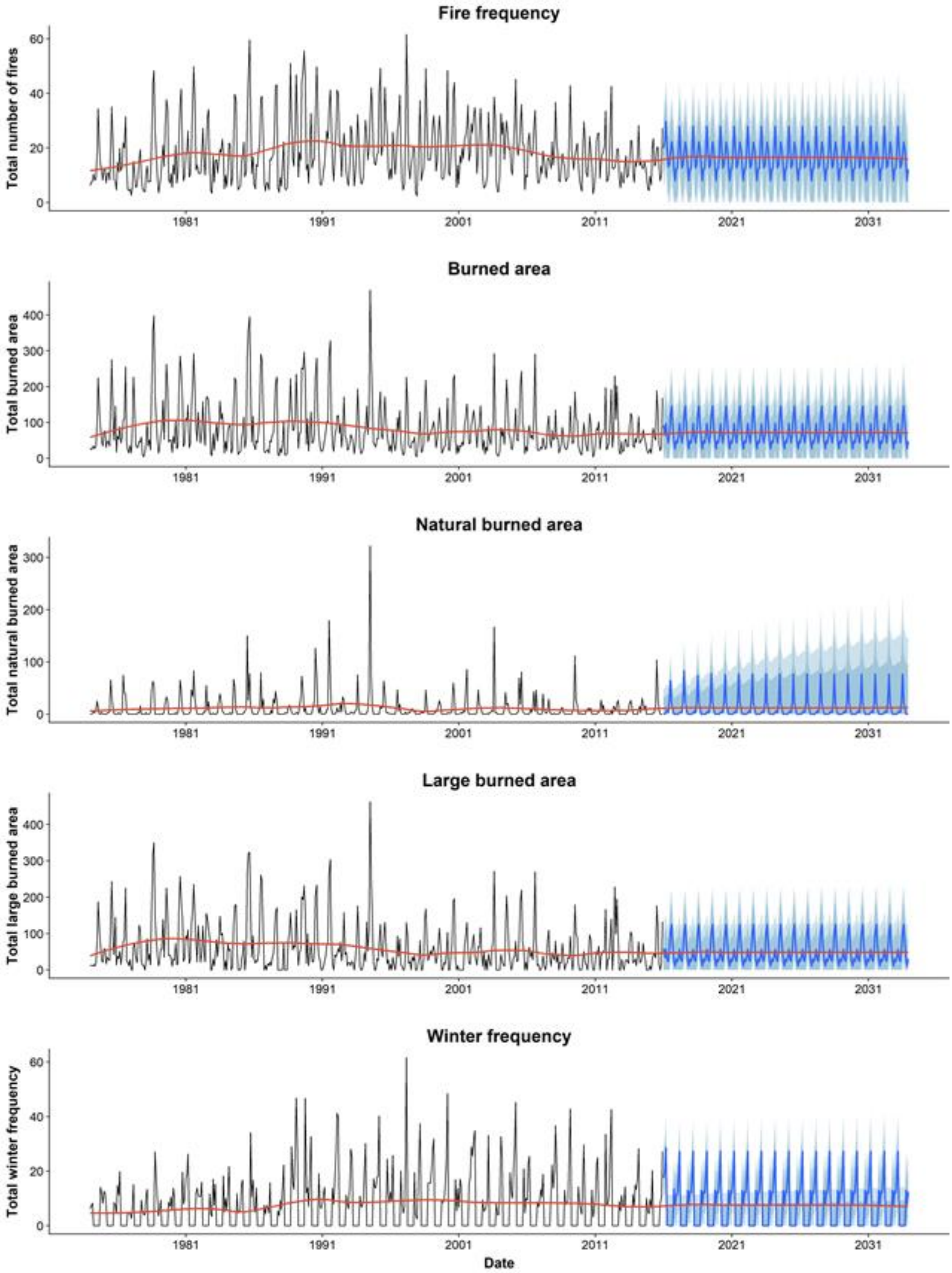

Fig. 2. Temporal evolution of fire features during the historic period (black line) and the near future (ARIMA forecast, blue line) mean with its corresponding upper and lower limits at 80% and 95% (in dark blue and light blue, respectively). Original values have been transformed to their square root. Red line represents the moving average.

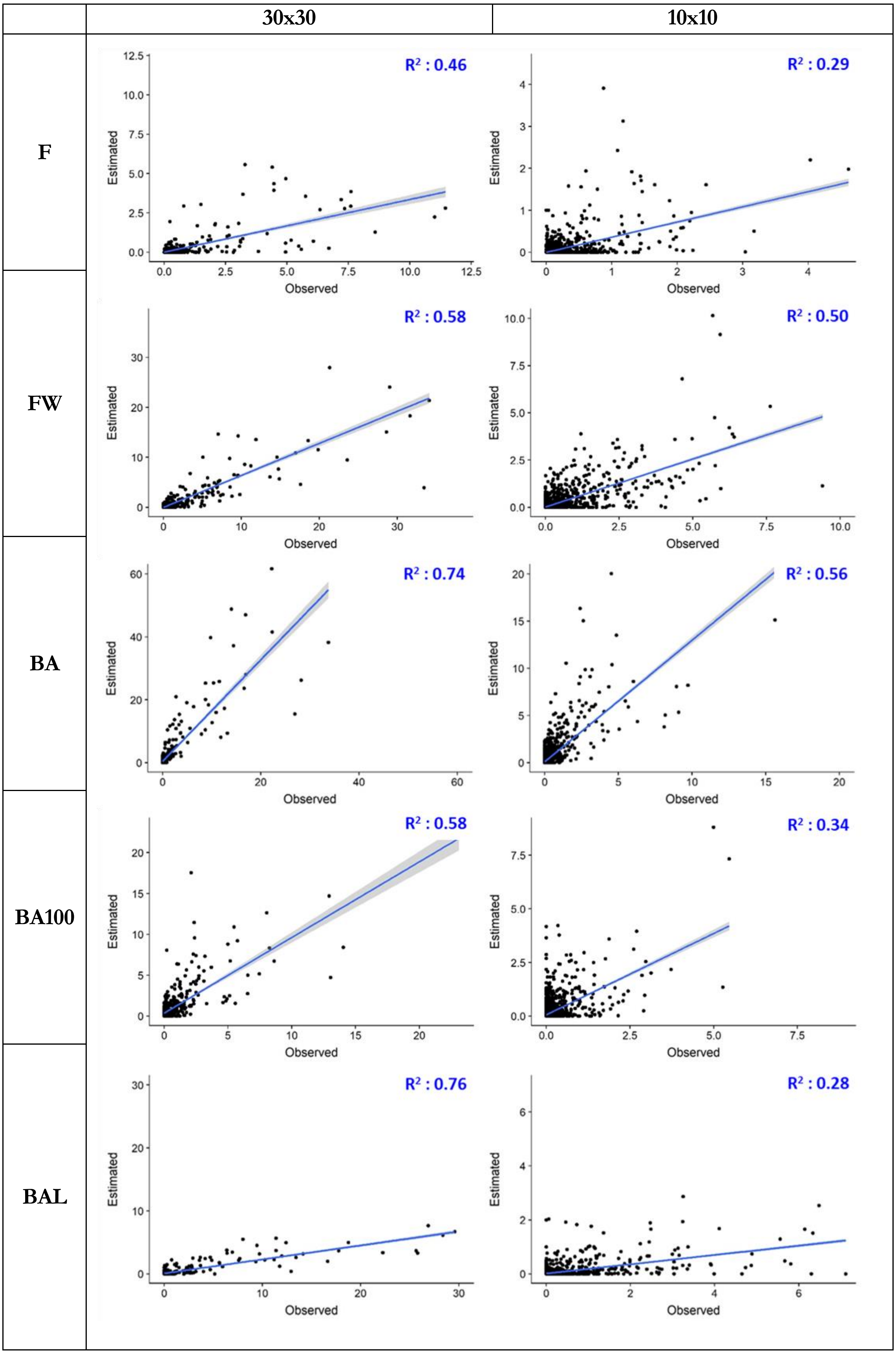

Fig. 3. Scatter plots and Pearson's R^2 coefficients between observed and predicted of ARIMA for each fire features at both grid sizes (left: 30x30 km; right: 10x10 km) in the period 2005-2015.

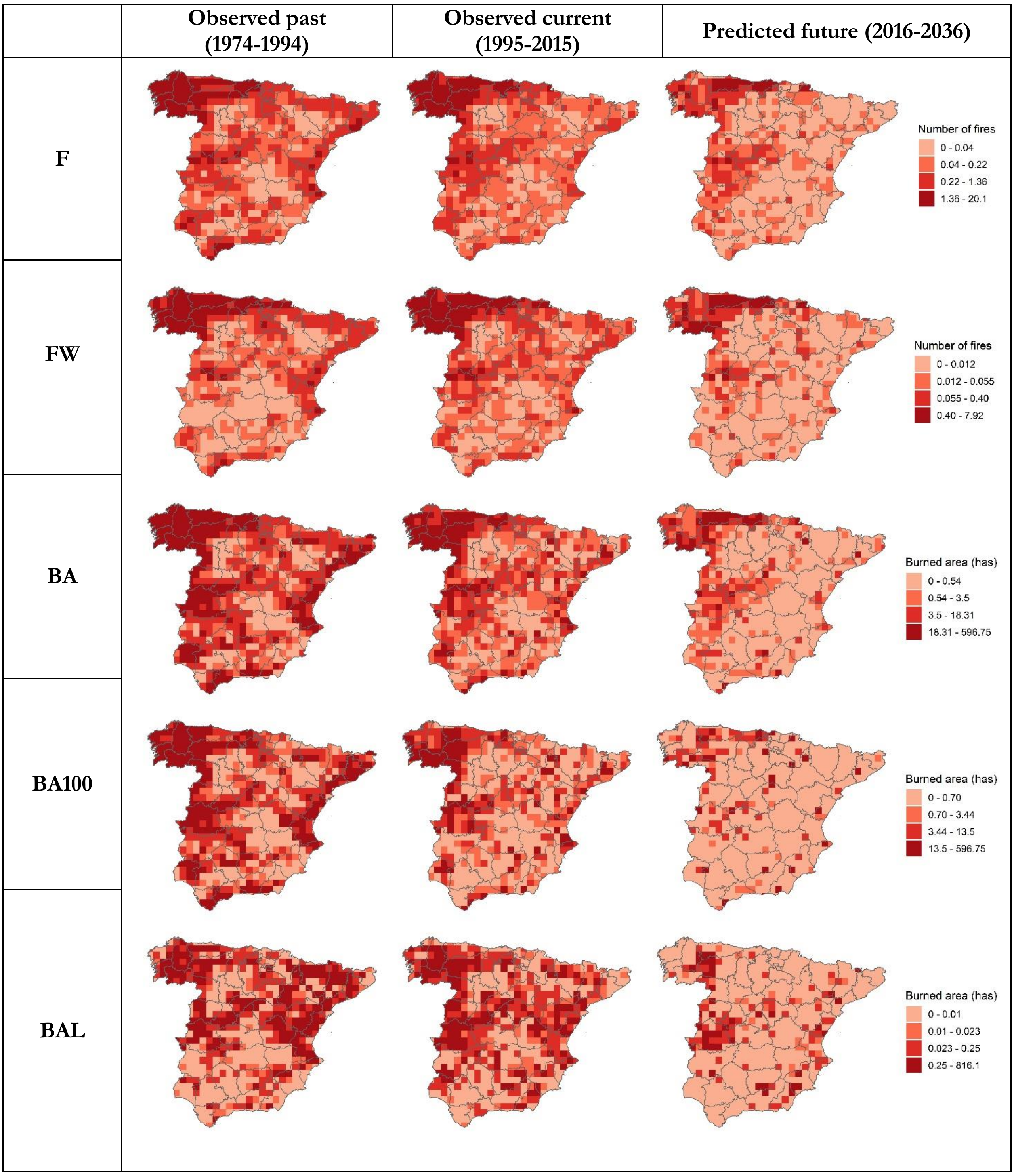

Fig. 4. Spatial distribution of mean values for each fire feature in the three periods of analysis and the administrative boundaries of NUTS3 level.

3.2. Spatial-temporal evolution of fire regime zones

Fire features in the current period were submitted to PCA and cluster analysis to outline homogeneous zones of fire activity. We selected three components from the PCA analysis, gathering up to 98% of the variance (Table 2). The first component (67.2% of the variance) relates to overall fire activity with moderate loads in all features, excluding natural fires, while being the sole component relating to winter fire occurrence. Overall, this component was considered to depict the gross of human-caused fire activity. The remaining two components accounted for natural and large fires, respectively. Component 2 (21.5% variance) positively correlated with BAL and BA100, suggesting that natural fires were somewhat linked to large fires. Component 3 (10.5% variance), correlates positively with both large fires and overall burnt area. Both PC2 and PC3, displayed opposed correlation between the highest ranked features (BAL and BA100, respectively) and winter fire activity, which indicates that either natural or large fires were better linked to summer season.

Cluster analysis yielded a total of four clusters, i.e., fire regime typologies (Fig. 5 and Table 3), one less than those obtained in Part 1 due to the disaggregation of the intermediate fire activity cluster (type 3, Part 1) into 'adjacent' clusters (types 2 and 3, Part 2). Clusters were ranked from 1 to 4 according to its hazardousness. Cluster 1 gathered those locations with low fire activity. Cluster 2 was composed of Medium-sized wildfires starting in summer with slight contribution of lightning-caused fires. Cluster 3 collected those cells with the greatest occurrence of large fires and natural-caused fires. The last cluster depicts large fire occurrence and burned area, with almost no contribution of natural fires and with the highest incidence of winter fires. In terms of spatial extent, low-to-moderate fire activity situations (clusters 1 and 2) were the most frequently observed (38% of cells each). Clusters depicting high fire activity (clusters 3 and 4) accounted for 24% of the cells together.

Table 3. Summary of cluster description. F: fire frequency, FW: winter frequency, BA: burned area, BA100: large burned area, and BAL: natural burned area. Bold numbers indicate average values whereas median appears in italics.

Cluster ID	Cells	%	F	FW	BA (ha)	BA100 (ha)	BAL (ha)
1	205	37.6	**0.10**-*0.06*	**0.03**-*0.01*	**0.96**-*0.39*	**0.33**-*0.00*	**0.03**-*0.00*
2	208	38.2	**0.27**-*0.19*	**0.08**-*0.05*	**5.09**-*3.83*	**3.30**-*2.23*	**0.31**-*0.06*
3	80	14.7	**1.25**-*0.61*	**0.51**-*0.15*	**43.48**-*31.52*	**32.61**-*26.56*	**4.42**-*2.46*
4	52	9.5	**5.14**-*4.63*	**2.63**-*1.92*	**61.45**-*44.01*	**25.81**-*11.53*	**0.29**-*0.09*

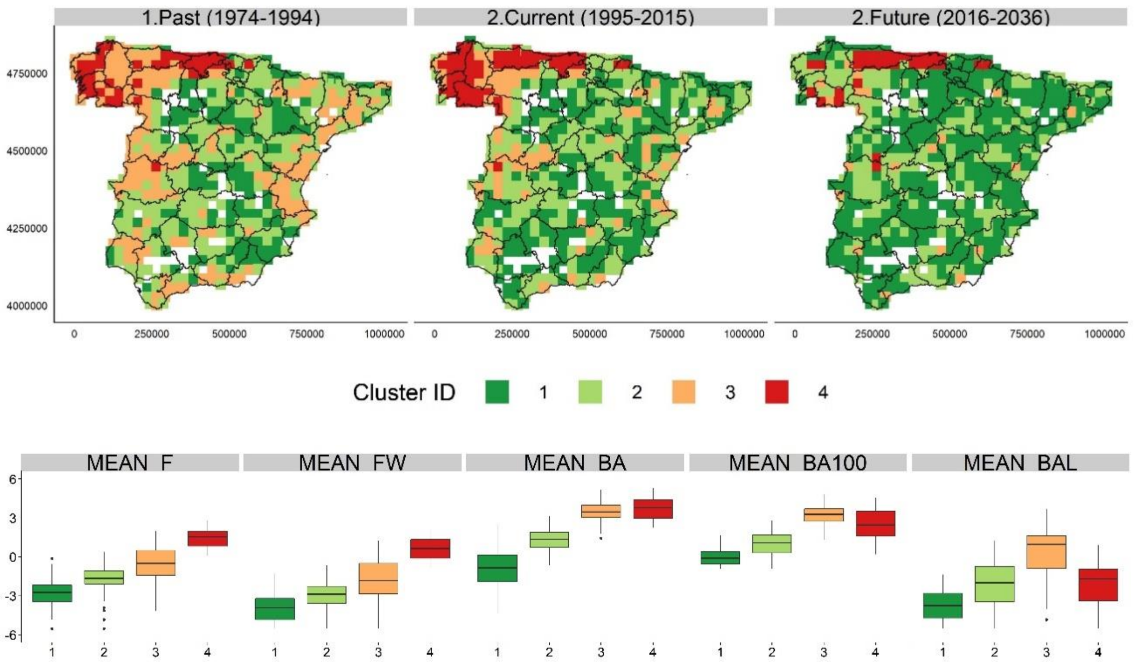

Fig. 5. Top: spatial distribution of clusters in the three periods. Bottom: distribution of fire features per cluster (values were log-transformed to enhance visualization). F: number of fires; FW: number of fires during autumn-winter season; BA: overall burned area; BA100: burned area from large fires (>100 ha); and BAL: burned area from natural-caused fires.

Fig. 6 and Table 4 summarize the observed cluster transitions and their spatial distribution across periods. The KNN classification yielded a good agreement with an average accuracy of 89.6% and a Kappa coefficient around 0.80 (Altman, 1991). Lower fire activity (cluster 1) advanced across the hinterlands towards the Mediterranean from past to future (110 cells in past-current and 176 current-future, out of 545). Medium-sized fires (cluster 2) were confined to the hinterlands during the past, progressing over the Mediterranean coast in the current period (62 cells). In the future, its footprint was predicted to reach some areas of Galicia transitioning from cluster 3 to 2 (36 cells). Large and natural fires (cluster 3) were the most frequent situation in the past, covering vast regions in the Northwest, the western hinterlands and most of the Mediterranean coast. However, its extent has greatly declined towards present, mostly replaced by medium-sized and natural fires. This typology was envisaged to be the least frequent in the near future, confined to some locations in the Northwest and small enclaves within the Mediterranean and the Central Mountain Range. Finally, cluster 4 covered mainly the northwestern area, reaching its largest extension in the current period. We foresaw the persistence of this situation along the northern Cantabrian cornice, and sparsely located in a small number of cells along the border with Portugal.

Overall, low fire activity gained importance over time (2-1: 80 cells past-current and 147 cells current-future, but also 3-1: 30 cells and 29 cells). Natural fires were expected to decrease in size (3-2: 62 cells in past-current and 36 cells in current-future), but at the same time they showed a modest increase in overall area during the next twenty years (2-3 with 14 cells past-current and 5 cells in current-future). On the other hand, regions experiencing a minor increase in fire activity will be likely in the future (1-2: 64 cells) with a moderate enlargement of fire size during summer in the hinterlands. In turn, the highest fire activity (cluster 4) was envisaged to persist along the northern coast (27 cells), though some spots will transition towards decreased fire incidence in the future (4-2: 16 cells). Pathways leading to increased winter fires (leading to cluster 4) were commonly observed in past-current transitions, but less frequent in current-future. Conversely, naturalization of fire cause (4-2 and 4-3) were expected more often in the current-future transition. Finally, the most stable fire regimes were clusters 2 and 1 from past to current and cluster 1 in transitions into the near future.

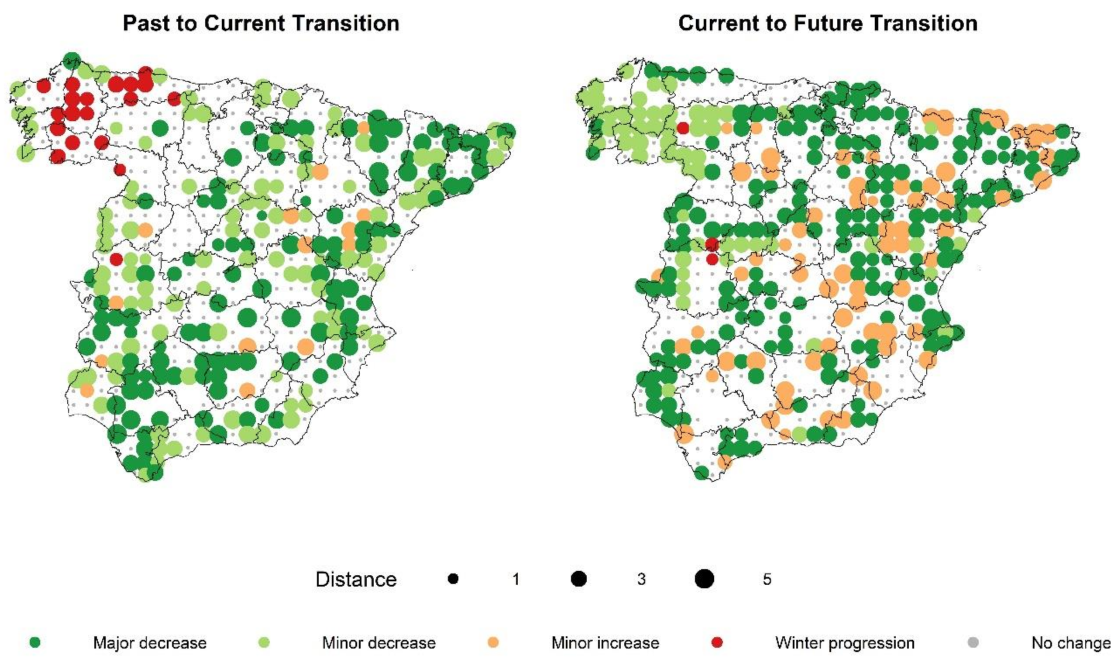

Fig. 6. Cluster transitions (CT) more frequent and magnitude of change (in Canberra distance) between current clusters and past-future fire features.

Table 4. Transition matrixes between past-current and current-future clusters. The most frequent CT were highlighted in bold. Color depicts overall trajectories. Major decrease: dark green; minor decrease: light green; minor increase: orange; winter progression: red). The grey cells correspond to no-change.

Past \ Current	1	2	3	4	Total
1	95 *75.4%*	**29 *23%***	2 *1.6%*	0 *0%*	126 *100%*
2	**80 *38.3%***	113 *54.1%*	14 *6.7%*	2 *0.9%*	209 *100%*
3	**30 *17.5%***	**62 *36.3%***	60 *35.1%*	19 *11.1%*	171 *100%*
4	0 *0%*	4 *10.2%*	4 *10.2%*	31 *79.5%*	39 *100%*
Total	205 *37.6%*	208 *38.2%*	80 *14.7%*	52 *9.5%*	545 *100%*

Current \ Future	1	2	3	4	Total
1	141 *68.8%*	**64 *31.2%***	0 *0%*	0 *0%*	205 *100%*
2	**147 *70.7%***	56 *26.9%*	**5 *36.2%***	0 *0%*	208 *100%*
3	**29 *36.2%***	**36 *45%***	12 *15%*	3 *3.7%*	80 *100%*
4	6 *11.5%*	**16 *30.8%***	3 *5.8%*	27 *51.9%*	52 *100%*
Total	323 *59.3%*	172 *31.5%*	20 *3.7%*	30 *5.5%*	545 *100%*

4. DISCUSSION

In this work, we conducted the multitemporal outline of homogeneous fire regime typologies and zones in mainland Spain to a) outline fire regime zones for past and current periods, b) predict their immediate future evolution, and c) analyze the main transitions in terms of spatial and temporal patterns. We aimed at improving the identification and definition of fire regimes in Spain, as well as providing insights into the effects the current of fire suppression policy. A better knowledge of the fire regimes involves not only assessing their geographical distributions but considering a temporal framework able to reflect ongoing changes resulting from policy and managerial practices. To the best of our knowledge, this, and the complementary work from Part 1, were the first attempts to investigate spatially explicit temporal dynamics of fire regimes exploring the near future evolution.

Same as in Part 1, the methodological approach sufficed to capture the spatial (cluster plus KNN) and temporal (ARIMA) patterns of fire regimes (Kappa ≈ 0.8). In turn, ARIMA faithfully outlined both the temporal and geographical arrangement of fire features, yielding a good predictive performance (R^2 ranging from 0.48 to 0.76). However, the size of the spatial unit of analysis had to be downgraded to ensure the consistency of ARIMA projections (Fig. 3). Fire regime typologies remained mostly equal, although the number of fire regimes reduced to 4 due to the disaggregation of human-related intermediate activity (type 3 in Part 1). Nonetheless, the nature of the remaining regimes was consistent with Part 1 (see Fig. 3 Part 1 and Fig. 5 Part 2).

ARIMA modeling anticipated a generalized drop in all fire features (A. Jiménez-Ruano et al., 2017a; M. Rodrigues et al., 2013; San-Miguel-Ayanz et al., 2017; Silva et al., 2019; Turco et al., 2016). Silva et al. (2019) reported a decline in burned area as a direct effect of the intensification of fire suppression, promoting the rebound of forest area (i.e., fuel accumulation) as a side effect. It is well known that fire suppression in Spain (and most countries in the European Mediterranean region) has been overemphasized since the mid-90s, as a result of an extraordinary fire wave (Badia et al., 2002). Our findings were consistent with the overall decrease forecasted in fire incidence, particularly patent in features depicting burned area size (A. Jiménez-Ruano et al., 2017a; Turco et al., 2016).

Of course, the change in fire regime was not expected to be spatially stationary, nor was it between historical periods (past to current) neither towards the near future. During the historical period, we observed a pattern very similar to that from Part 1, with a generalized drop in fire activity in the hinterlands and the Mediterranean coast, the most densely populated area of Spain. Since the mid-90s, suppression and prevention have been increasingly funded (MAGRAMA, 2012) aiming at protecting human assets often located within the wildland-urban interface (Alcasena et al., 2019). The WUI region is often considered a priority protection target due to the increased presence of people and housing (Darques, 2015; Salis et al., 2014). Due to its specificities, the WUI acts both as a source of potential fire ignitions from increased pressure on wildlands (Leone et al., 2003b) but at the same time it facilitates accessibility to firefighting brigades, thus enhancing fire containment. For instance, the most frequent transitions where those coming from fire regimes dominated by large fires with fair contribution of natural-caused fires towards medium-sized fires (3-2) or even low fire activity (1-2), especially in the Mediterranean. On the other hand, a progression towards anthropogenic fires was detected in Galicia (Northwest end of Spain). The most prominent change in that zone followed the path from fire regime 3 to regime 4, i.e., from large and natural fires towards increased fire counts, overall burnt area and increasingly hazardous winter season. This transition is most likely related to accidental fires associated agricultural labors (Moreno et al., 2014; Prestemon et al., 2012; Rodrigues et al., 2018). From a fire regime perspective, we considered the transition '3-4' as a progressive (worsening) one given the increased impact of human-caused fires. The foretold pattern of transition towards the near future resembles the historical one, with decreased fires, especially along the Mediterranean. The Northwestern region, known as the area with highest fire activity within Spain, is likely to experience a shift towards more frequent intermediate-size fires during summer. The sole exception appears in the Northern coast, which was expected to maintain similar fire regimes in the future, with persistent winter fire activity (González-Olabarria et al., 2015; Rodrigues et al., 2018), suggesting increasing role of human activities (Turco et al., 2018).

Despite the overall observed and expected decrease in fire incidence we do not intend to be indulgent nor minimize the impact of the fire hazard phenomena. The observed patterns and trends would most likely involve several undesired effects. A wide fraction of wildfire managers and practitioners warn about the unforeseen consequences of a sustained total fire exclusion policy. The main side effect relates to fuel accumulation, particularly in abandoned agricultural lands (Pausas and Paula, 2012) but also in those zones in which the natural fire regime was disrupted (Fréjaville and Curt, 2017), thus consistently excluded from burning (Piñol et al., 2005). The progression of forested lands coupled to more hazardous climate, envisaged by most long-term climate projections (Vicente-Serrano et al., 2014), may eventually lead to a raise in the frequency devastating and severe fires (Costa et al., 2011; San-Miguel-Ayanz et al., 2013) potentially threatening forest resilience (Stevens-Rumann et al., 2018). In a context of increasing funding of firefighting means, a shift towards a more proactive management of fuels is recommended. Forest management is becoming increasingly linked to fire management, progressively integrating prescribed burns or fuel control into management strategies. Our findings may serve as guideline to identify 'fire-excluded' regions, i.e., those areas displaying the most pronounced declining trajectories that would eventually lead to increased fuel loads. The careful inspection of observed (past-current) and predicted (current-future) changes in fire regimes can be very informative to further analyze the relative role of fire drivers (land use, climate, vegetation and topography) and their complex interplay (Morgan et al., 2001b).

However, our proposal has some limitations that must be clearly stated. The spatial unit of analysis was rather coarse after downgrading from the original 10x10 km resolution. Despite it sufficed to capture the nature and distribution of fire regimes, it may preclude more in depth analyses such as explanatory regression models of fire regime change (similar to those from Part 1). We assumed a conservative scenario of evolution that projects the current evolution of drivers but, even though it is likely to happen, it is not necessarily going to be case. Furthermore, we extended the observed trend until twenty years beyond the historical period but that trend may 'stabilize' earlier. In that case, we might be overestimating the magnitude of the forecasted decline.

5. CONCLUSIONS

The current research belongs to a series of two manuscripts aiming at describing spatial-temporal dynamics of fire regime and its drivers in Spain. In this work, we proposed the first attempt to outline fire regime zones that incorporates a temporal perspective towards the near future. We investigated three different temporal spans. Two historical periods, i.e., past (1974-1994) and current (1995-2015), which were built from historical fires (>1 ha), and a third located in the future (2016-2036), projected from current observations.

We identified four fire regime typologies depicting (i) low fire activity, (ii) medium-sized wildfires starting in summer with slight contribution of lightning-caused fires, (iii) large fires linked to natural-caused fires, and (iv) large fire incidence linked to winter activity. These four typologies were spatialized in the three aforementioned periods to ascertain the most frequent trajectories of fire regime change. As in Part 1, regressive trajectories (decline in fire activity) were the most common pathway into the future, with a significant increase of zones with low fire activity. Nonetheless, fire regimes linked to winter activity were observed to advance in the Northwest, being expected to persist along the northern coast.

From a managerial perspective, our results allow identifying priority intervention areas that may experience fuel accumulation, leading to more hazardous conditions and increased chances of large fires in the future.

Declaration of Competing Interest

The authors have no conflicts of interest to declare.

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CHAPTER 9: TRANSLATING FIRE REGIME ZONING SCHEMES INTO PYROREGIONS

This chapter summarizes the final delimitation and characterization of the pyroregions in mainland Spain, based on the previous fire regime typologies and trajectories obtained. Moreover, it adds the spatial overlapping of climatic, topographical and human factors more related to fire activity to offer a complete pyrogeographic entity. The methodology has been based on geo-processing tools in a GIS framework.

Mapping recent pyroregions on the basis of spatial-temporal patterns of fire regimes and environmental-human datasets in mainland Spain

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Abstract

The geographical delimitation of pyroregions (homogenous fire regime regions) and their temporal evolution is an important task in forest fire research. First, it requires an adequate selection of fire features and drivers; and second, the evolutionary dimension must be included. This article presents a collection of geographic datasets in a map format created by GIS tools. It includes the first map of pyroregions where fire regime trajectories over time are included. In addition, reclassified environmental (temperature-precipitation trends, average elevation and slope) and human variables (WAI, WUI and Demographic Potential percentage of variation) were overlapped onto the fire regime transitions. The final pyro-geography scheme consists of 4 general pyroregions with 16 sub-regions, comprising a complete description of fire regime in mainland Spain and the underlying fire drivers. The novelty of this data brings the opportunity for fire-forest management in other countries to apply a similar dataset on a national scale in order to outline their pyroregions.

Keywords

Pyroregion, pyro-geography, fire regime, spatial modeling, Spain

1. Data

The data presented here shows the spatial distribution of the pyroregions in mainland Spain (Fig. 4), which includes the most important fire regime trajectories detected over time. In addition, each of the environmental-human variables is introduced in map format. Environmental factors (Fig. 1) consist of climate dynamics, more specifically trends in the average temperature and precipitation (over the 1974-2010 period) and topographical aspects (such as average elevation and slope) which are crucial for fuel distribution, accessibility and fire propagation potential. Finally, anthropogenic drivers are depicted by variables related to human pressure on wildlands: wildland-urban interface (WUI, top left Fig. 2), the rate of variation in demographic potential (DP, bottom left Fig. 2), the existence of agricultural activities close to forested areas, and wildland-agricultural interface - (WAI, top right Fig. 2).

2. Experimental Design, Materials, and Methods

The project design was based first on the characterization of 7 environmental-human variables from different data sources (see following subsections for more details) strongly linked to the spatial-temporal behavior of fire regimes in Spain. These factors were selected by the Random Forest regression with the most frequent fire regime trajectories, see Rodrigues et al. (unpublished results), for more details. In addition, each of these environmental and human factors were reclassified into three major categories. Low-medium-high for WAI, WUI, elevation and slope; and decreasing, stable and increasing for the climatic trends (temperature and precipitation) and Demographic Potential (DP) rate of variation. Environmental-human mapping was carried out by applying a forest mask to discard grids with less than 25% forest area.

2.1. Climatic factors

We extracted the climatic and topography information from different databases. For climatic variables, the average monthly temperature was retrieved from the MOTEDAS database (González-Hidalgo et al., 2015), spatialized using a 10x10 km grid, which was assigned to our grid according to the nearest neighboring cells. Next, the temperature trend was estimated by means of Sen's slope (Sen, 1968) of the maximum (daytime) temperature for the period 1917-2010. The average monthly temperature was retrieved from the MOPREDAS database (González-Hidalgo et al., 2011) and also assigned to our 10x10 km grid following the nearest neighboring cells method. As with temperature, we calculated the Sen's slope to obtain temporal dynamics in rainfall for the period 1974-2010.

2.2. Topographical factors

Both elevation and slope were retrieved from the GTOPO30 1 km Digital Elevation Model (Earth Resources Observation and Science Center/U.S, 1997). The first variable refers specifically to meters above sea level, and the second to percentage rise elevation calculated from the elevation layer. Both variables were resampled from the original 1 km resolution to the 10x10 km grid as the average value of all pixels within a cell.

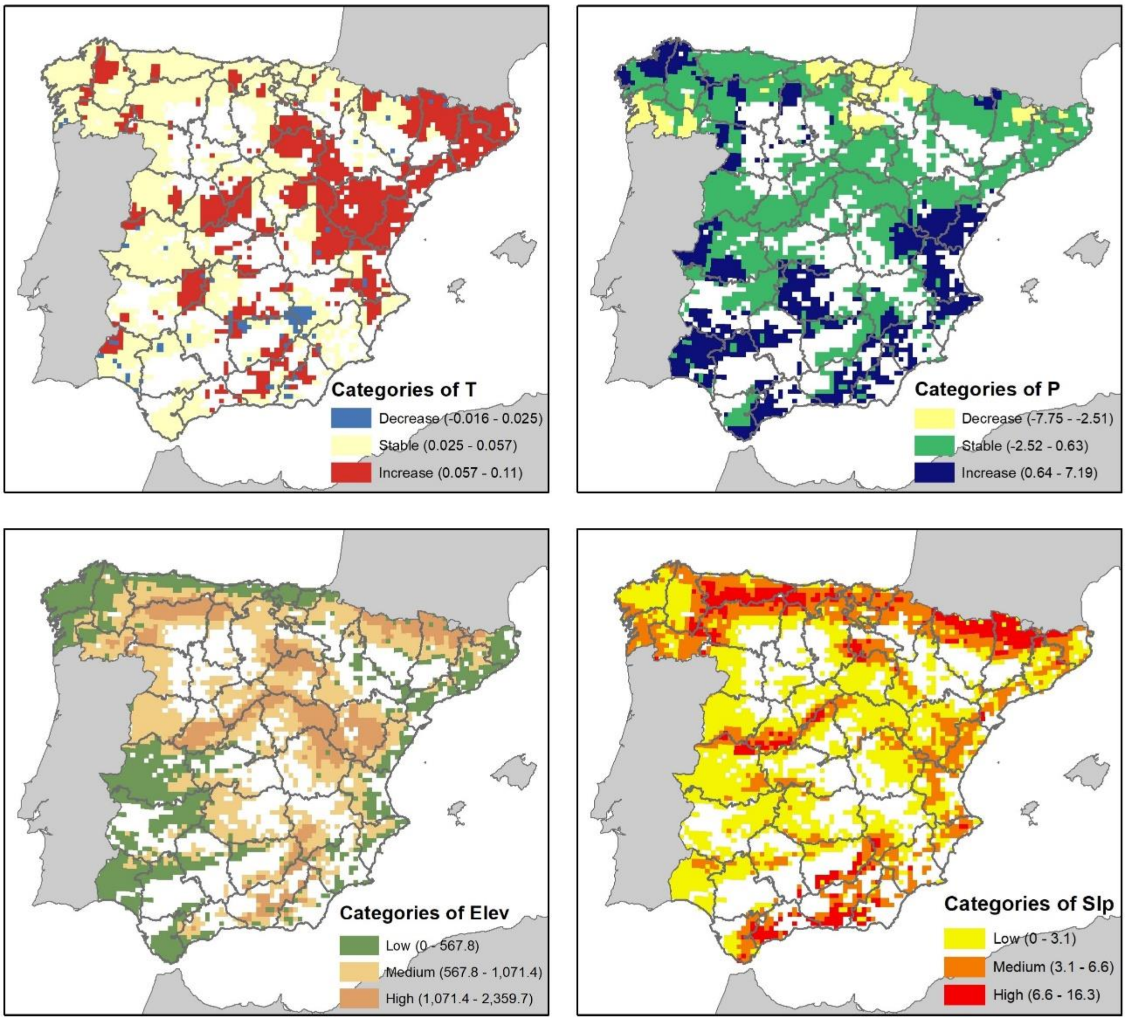

Fig.1. Spatial distribution of reclassified environmental and topographical fire drivers. Top left: temperature trend, top right: precipitation trend, bottom left: elevation, bottom right: slope

2.3. Human factors

The Corine Land Cover 1990 was used to outline both the Wildland Agricultural Interface (WAI) and Wildland Urban Interface (WUI). The first refers to the length in meters of the boundary line between agricultural lands and forest areas, and the second to the length in meters between urban settlements and forest areas. On the other hand, the Demographic potential is a dimensionless variable which reflects the demographic power as well as the ability to provide population growth in the near future (J. L. Calvo and Pueyo, 2008). The original database was estimated at 5x5 km resolution; thus we have resampled it to 10x10 km according to the average value. The final demographic potential was expressed as the rate of change between 1991 and 2001.

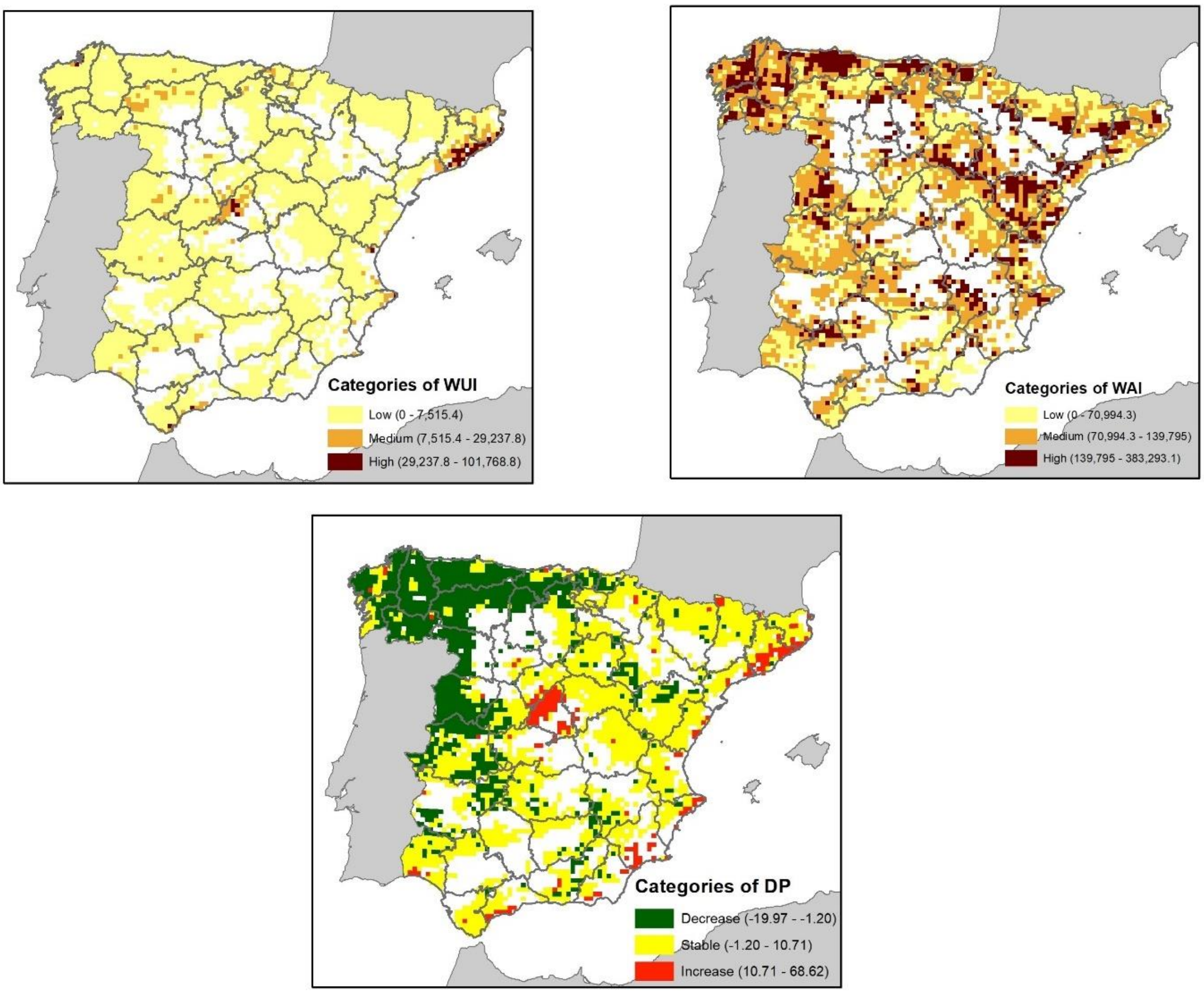

Fig. 2. Spatial distribution of the reclassified Wildland Agricultural Interface (WAI)

<u>2.4. Mapping pyroregions</u>

For the construction of the pyroregions map several phases were carried out (Figure 3):

1) We gathered all the fire records from the EGIF database for the period 1974-2015, the longest time span available when conducting this research. It is important to note that all fire events below 1-hectare were excluded from the process to avoid temporal inconsistencies, since those were only registered systematically after 1988.

2) We split the original data into two different datasets, according to Jiménez-Ruano et al. (2017a) and Fréjaville and Curt (2017), who found a significant change point in the evolution of fire activity in the mid-1990s. Therefore, the periods obtained were 1974-1994 and 1995-2015 (from now on referred to as past and current).

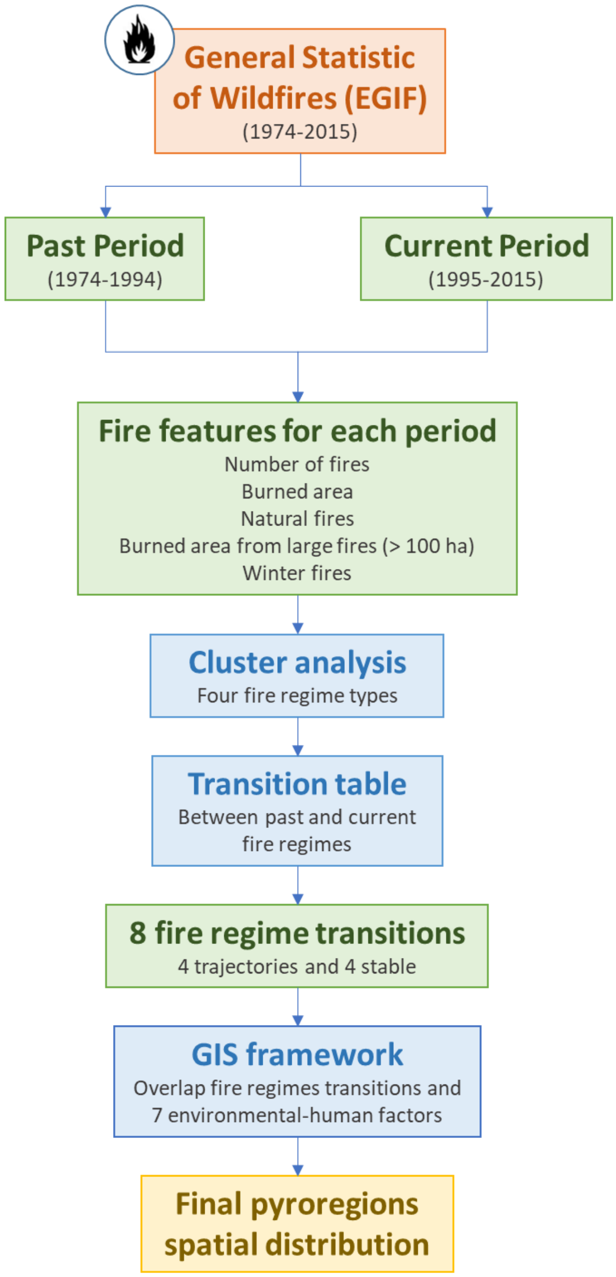

Figure 3. Workflow of the mapping pyroregion process.

3) For each dataset, we extracted information on the number of fires, burned area, natural fires, large fires (burnt area over 100 hectares) and fires occurring during winter (October to March). Finally, from this data we computed five fire features on a 10x10 km grid level: fire frequency (F), winter frequency (FW), burned area (BA), burned area by large fires (BA100) and burned area by natural cause (BAL).

4) Cluster analysis produced five fire regime types on a 10x10 km grid and four typologies on a 30x30 km grid. We finally decided to focus on the coarser spatial unit (30x30 km) in order to outline the main fire regime types, thus using 4 typologies of fire regime transitions. These four categories of fire regime trajectory are ranked according to the danger they pose.

5) A transition table related the different grids from the 4 fire regime types between past and current periods obtained a total of 8 final fire regime transition zones (1, 2, 3 and 4) and their corresponding stable ones (1-1, 2-2, 3-3 and 4-4) for the whole period (1974-2015).

6) The last step was obtaining the final delimitation of pyroregions by geo-processing tools in a GIS framework. The main task was the spatial overlapping between the 8 final fire regime transition zones with respect to the 7 environmental-human factors.

1.1. General and sub-pyroregions

The scheme of pyroregions was designed using two hierarchical levels and defining general regions according to overall transition paths reported by Rodrigues et al. (unpublished results) and Jiménez-Ruano et al (unpublished results), later dividing them into minor subregions characterized by local drivers and conditions (Figure 4).

A geographical and toponymical description, with its specific fire regime description coupled with the contribution of environmental-human fire drivers is provided for each subregion. As a result, we obtained a total of 4 general pyroregions and 16 sub-pyroregions characterizing the fire regime in mainland Spain. A detailed description of each of these pyroregions and sub-regions is given below, beginning with a description of the general regions in terms of the geographical context within mainland Spain, and concluding with a presentation of the overall trajectory of fire activity and the characterization of the most influential fire drivers.

(1) Northwest Atlantic. This general pyroregion is located in the Northwest, Cantabrian Cornice and the west of the provinces of León and Zamora and is divided into 4 different sub-pyroregions.

1.1. Atlantic Galicia: This pyroregion is located in the western half of Galicia and province of Ourense. It is characterized by an intensified and persistent winter fire regime. In terms of the fire drivers, the region presents a medium-high WAI, a low WUI, a generalized decrease in the DP – although stable in the low estuaries-, a stable temperature but with a south-north gradient from a decreasing to increasing precipitation tendency. Finally, elevation is generally low, but there are medium altitudes in the province of Ourense with low-medium slopes across the whole region.

1.2. Cantabrian Cornice: This covers the north face of the Cantabrian Range, more specifically the Autonomous Communities of Asturias and Cantabria. It is notable for its strong trajectory towards winter fire activity and maintaining that progression over time. In terms of fire drivers, it has the longest WAI in northern Spain, a low WUI, a general decrease in DP, although some are stable on the Cantabrian coast. Climatic trends show stability for temperature and precipitation, but in Cantabria, a general decrease in rainfall is found. Finally, this region has an elevation gradient from flat coastal areas to the high altitudes of the Cantabrian Range, resulting in a generally rugged landscape.

1.3. León and Zamora: This sub-region is located in the western half of the inland provinces of León and Zamora, as well in the south-eastern corner of Lugo. It can be considered as a transition region between purely Atlantic and Mediterranean conditions. For this reason, it has mixed fire activity trajectories, although the persistence and tendency towards minor increases in forest fires is especially noticeable. From the point of view of the driving factors, it displays a general low-medium WAI, an overall low WUI (although with medium areas in León), and a decline in DP. Temperature is generally stable with some areas of increases in the western mountain ranges. Rainfall presents a similar picture, although with more and larger areas of increases. Finally, it is a region characterized by its medium elevations and high areas in the province of León, so that the latter has a slope gradient ranging from the flattest areas in the east to the steepest in the west.

<u>1.4. Northeast Galicia:</u> This region mainly covers the province of Lugo and the east of A Coruña. It is characterized by an overall minor decrease in fire activity. Drivers in this region exhibit a medium-high WAI, low WUI, a general decline in the DP, increases and stable trends both in temperature and precipitation. It is a flat region with both low and medium slopes.

(2) Inner Mediterranean. This upper pyroregion has the most extensive surface area, occupying most of the mainland hinterland. It is composed of a total of 6 sub-pyroregions.

<u>2.1. North plateau and Basque Country:</u> This sub-pyroregion is located in the north plateau, the Basque Country, western half of La Rioja and northwest of Navarre. In general, it shows a minor decrease in fire activity. With human drivers, high WAI can be found in the Basque Country, many areas of Salamanca, the north of Palencia and scattered over the province of Burgos, a medium agricultural interface occupies the remaining territory as well as the low WAI in mountainous regions. Demographic potential shows both stability (flat areas) and decreases (mountainous regions and western Salamanca). In terms of climatic trends, stable temperatures dominate the region with a few increasing enclaves (southwest Salamanca and north Burgos). The precipitation trend is stable in most of the region, although a noticeable decrease is found in the Basque Country and La Rioja, as well as a notable increase in an area in north Palencia. Finally, medium elevation and low slopes dominate this unit, but also high altitudes and steep slopes in the Cantabrian Range and the northwest of the Iberian Range. In turn, low areas are located in Basque Country.

<u>2.2. Ebro valley, Pre-Pyrenees and Lleida plain-highlands:</u> This region mainly covers the Ebro basin, specifically the provinces of Zaragoza, south of Navarre, most of Huesca, northeast of Teruel and the flat Pyrenean regions of Lleida. It is characterized by an overall decrease in fire activity, although it has scattered enclaves of minor increasing trajectories. Regarding human drivers, medium-high values of WAI dominate, with low values in the mountainous areas. A stable DP is the main category, although some falls are found in the southwest of Zaragoza and northeast of Teruel. Climate tendencies in the region exhibit a general rise in temperature, and stability in the rest. Precipitation trends are stable, except for part of Pyrenees of Lleida, where they are falling. Finally, the topography gradient ranges from low, flat areas in the Ebro valley to higher, steep slopes in the Pyrenees.

<u>2.3. Eastern of Castilla-La Mancha:</u> This covers the southwest face of the Iberian Ranges, more specifically part of the provinces of Guadalajara, Cuenca, Albacete and some inland areas of Valencia. It is characterized by an overall minor decline in fire activity. In terms of fire drivers, WAI depicts medium and some high values, low WUI and stable DP. In turn, stable and rising (east of Albacete and southeast of Cuenca) temperatures are found in this region, whereas a general stability in rainfall predominates with some increases in mountain areas. Finally, medium elevations and low slopes are found.

2.4. Extremadura and North-Andalusia: This sub-region is located in the north of the Andalusian provinces of Jaén and Córdoba, as well as the eastern half of Extremadura. It shows a general minor decrease in forest fires. From the point of view of human drivers, this region generally has a medium WAI, low WUI and stable DP with some decreases in southeast Caceres, some enclaves in Badajoz and the southwest of Albacete. Climatic trends display mainly stable temperatures, but also falling in southwest Albacete-northeast Jaén and rising in the northwest of Jaén-east of Córdoba. In turn, rainfall shows both stable (east of Cáceres, Badajoz and Jaén) and increasing trends (hinterlands of Cáceres and Córdoba, as well as the south of Badajoz).

2.5. Iberian, southern plateau and mountains: This region extends across the northeast face of Central System Range, the whole Iberian Range, the south plateau, hinterlands of the Murcia Region, the Betic mountain systems and the western half of the Sierra Morena. It is characterized by a general major decrease in fire activity. Fire drivers show medium-high WAI (mainly in the Iberian Range, Albacete, and northwest border of Andalusia), a generalized low WUI – although medium-size ones can be found in the south of Ávila (surroundings of Madrid). A stable DP dominates the region, with some increases in areas of Murcia and the south of the province of Avila, whereas decreases can be found in the western end of north Andalusia and in the east of the province of Badajoz. With climatic trends, a general increase in temperature can be found in the Iberian Range, in the Sierra of Guadarrama area, some enclaves of the Betic systems and the east of Badajoz, leaving the rest of the territory with a stable tendency. However, there are some decreases in temperature in the northwest of Córdoba and southwest of Albacete. On the other hand, precipitation shows a general stable trend over this region (mainly in the north half of Iberian Range, west Toledo, Albacete and east of Badajoz), although it is important to note the presence of extensive areas of rainfall increases in the northwest border of Andalusia, the Betic systems and the southern half of Iberian Range. Finally, elevation is mainly high-medium with some low altitudes in inland Valencia, Murcia, Badajoz and the south-western face of the Sierra Morena. In turn, flat areas dominate the region, although mainly medium slopes can be found in the mountain ranges.

2.6. Pyrenean mountain range: This region mainly covers the Central Pyrenees (north Huesca, northeastern Navarre and northwest Lleida). It is notable for a significant decrease and persistence of low fire activity. The fire drivers are notable for low WAI and WUI, a stable DP increasing in an enclave in northwest Lleida. With climatic factors, the temperature shows an increase with stable trends, while precipitation has more stable tendencies, with a region of increases between Huesca and Lleida. Finally, the outstanding topographical variables are high elevation with very steep slopes.

(3) Inner Mediterranean. This general pyroregion extends through the mountain area and surroundings of the Central System range. It is formed by 3 different sub-pyroregions:

3.1. Western Central System Range: This sub-pyroregion is located in the western half of the Central System mountains, more specifically in the north of Cáceres, the southeast of Salamanca and the southwest of Avila. It can be considered as an inner enclave that has experienced a progression of fire activity in winter. With human drivers, WAI shows medium-high values, a low WUI and a decline in the DP trend. The climatic drivers show that temperature is stable, although some increasing areas are found both in west-east extremes. Rainfall is predominantly stable, with an area of rising trend in the west. Finally, there is a topographical gradient from the southwest, with low altitudes, to the northeast with higher elevations, resulting in a predominance of both moderate and high slopes.

3.2. Central System Range area: This covers the middle part of Central System Range (south-half of Avila and southeast of Salamanca), the whole Autonomous Community of Madrid, as well as some areas in the north of Toledo and the west of the province of Guadalajara. Fire activity exhibits minor increases over the historic period. From the point of view of anthropogenic factors, this area is dominated by a mainly low-medium WAI, a low WUI in most of the territory but with medium-high values in the northwestern surroundings of Madrid. The DP presents a west-east gradient from decreasing (Salamanca-west Avila) to an increasing variation (areas near Madrid). Regarding climate variables, this region is dominated by rising temperatures, while a stable trend characterizes precipitation. Finally, high-medium elevations are prevalent together with low-medium slopes.

3.3. Northwest Extremadura: This specific sub-pyroregion is located mainly in the western half of the province of Cáceres. It is formed by two different enclaves that have certain similarities as well as differences. Fire activity shows a minor decrease in forest fires in the west, while in the east there is a mix of decreases and some enclaves of minor increases. With human drivers, medium-low WAI dominates the region, low WUI, and stable-decreasing DP variation. Temperature exhibits no significant trend, although there is a general increasing trend in precipitation on the west side, whereas stability-increases are found in the east. Finally, the area is flat with very low slopes.

(4) Levante and southwest coast. This last upper pyroregion covers the whole of the Spanish Mediterranean coast, as well as the Andalusian Atlantic coast. It comprises 3 sub-pyroregions:

4.1. Mediterranean corridor and southwest coast: This covers almost the entire Spanish Mediterranean coast, as well as the Andalusian Atlantic coast. In general terms, it is characterized by a minor decline in fire activity; however, throughout the region many small enclaves of minor increases can be found (especially in the provinces of Valencia and Huelva). Human drivers present a medium-high WAI predominating in the northeast and east of the corridor, whereas, low-medium WAI is more noticeable in the south. A similar picture is observed for WUI, where the highest urban contact is located on the Catalonian coast. In turn, stability and increases in DP dominate the sub-region. Climatic variables exhibit a general rise in temperature (concentrated on the Catalonian and Valencian coasts) and stability in the south. On the contrary, rainfall trends are stable on the Catalonian coast, while there is a rising trend on the Valencian and south coasts. Finally, elevations are predominantly low, although some medium-high altitudes are found in the hinterland of Valencia and along the south face of the Betic ranges. Slopes are in general moderate-high (rugged relief), with the exception of flat plains of Huelva.

4.2. Hinterlands of Girona and Lleida: This covers the western half of the province of Girona, the center-east of the province of Lleida and inland Barcelona. It is dominated by a general and remarkable decrease in fire activity. Human drivers display mostly medium-high WAI, low WUI and decreasing DP, although medium-high values of urban interface and increasing population variations are found in the coastal area of Girona. On the other hand, temperature shows a general rising trend, while precipitation tends to be stable. Finally, medium-high elevations and slopes dominate this territory.

4.3. Southern mountainous end: This sub-region is located in the extreme south of mainland Spain, covering Cádiz, the west of Málaga and south-eastern Seville. It stands out for its general and significant decline in fire activity. The anthropogenic factors show a low-moderate WAI and low WUI although a continuous corridor of medium-high urban interface can be found on the Mediterranean coastline. In turn, DP exhibits overall stability but with some areas of rising variation in the east coast. Climatic variables present no trend in temperature, whereas precipitation shows both increasing (east half) and stable (west half) trends. Finally, it is an area of low elevations with some medium altitudes in the province of Málaga, thus medium-high slopes dominate the rugged territory.

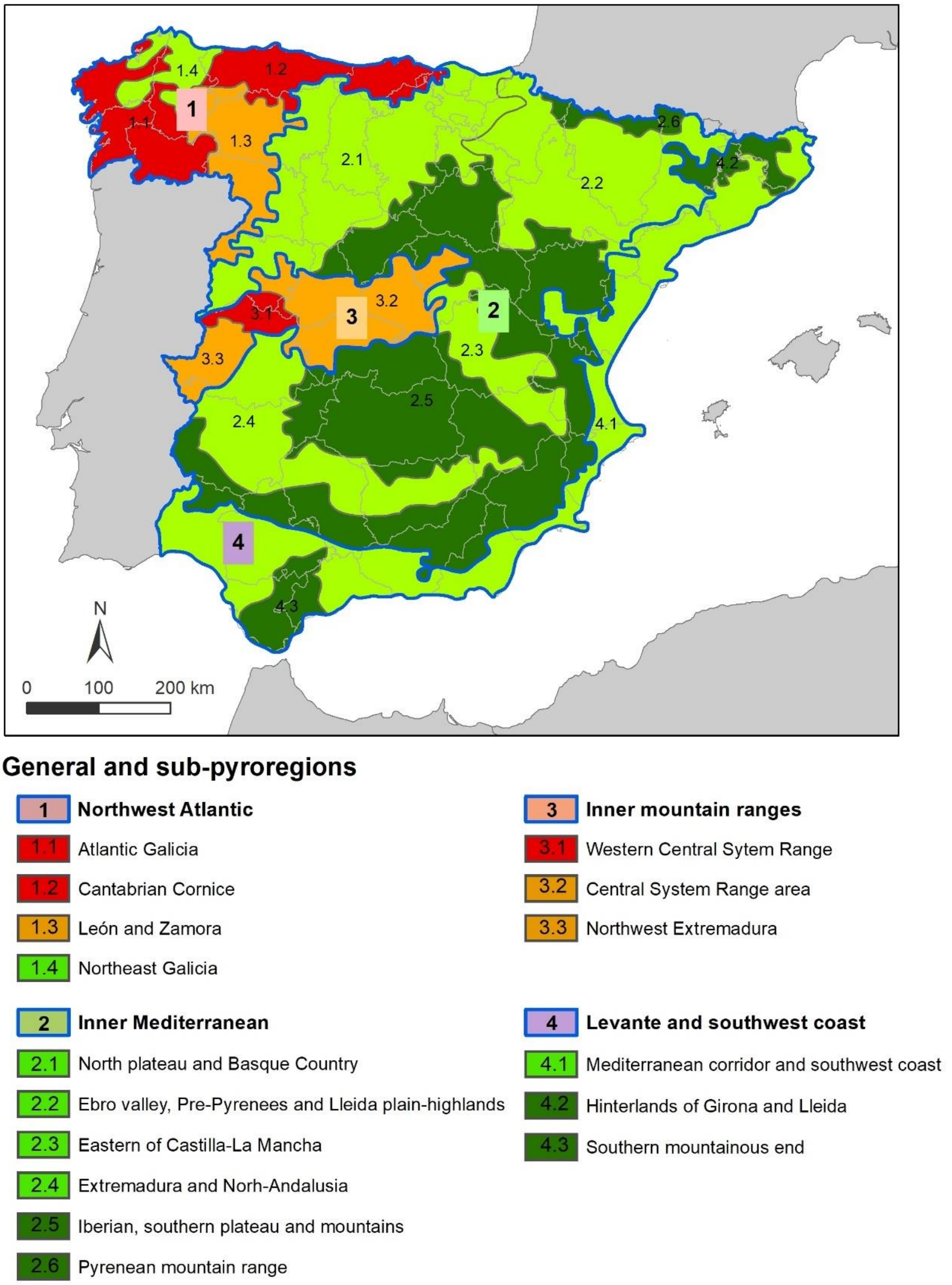

Figure 4. Spatial distribution of the 4 general pyroregions and their corresponding 16 sub-pyroregions.

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10 CHAPTER 10: CONCLUSIONS AND FUTURE RESEARCH

This chapter summarizes the main conclusions of this thesis as well as, presents potential future lines of a further research.

The methodologies employed in this PhD dissertation have sought to cover the following general purposes: a) to describe the spatial-temporal distribution of fire features that best characterize the general fire regime, b) to evaluate the contribution of meteorological danger in the temporal evolution of fire activity, c) to analyse the spatial-temporal changes of the influence of anthropogenic drivers in human-caused wildfires, d) to describe and characterize the evolution and causes of fire regime changes, and e) to obtain a general pyroregion map from the fire regime zoning.

Delimiting and characterizing homogenous fire regime regions (pyroregions) constitutes a laborious and complex task that must take into account various aspects of forest fires. Firstly, the selection of fire features, which is an important step as they have undergone spatial-temporal changes. Secondly, knowing which fire drivers are involved in the trajectories shown by wildfire regimes.

The temporal dimension of fire regimes was the cornerstone of the research. In this respect, we have proved that fire regimes are non-stationary, showing both trends and marked seasonality in certain regions of mainland Spain. Therefore, this has facilitated the identification of regions more prone to fires which, in certain cases, have also been shown to experience a lengthening of the summer fire season.

It is important to emphasize the strong potential of the methods employed throughout the investigation to characterize fire regimes. In particular, we highlight the performance of multivariate regression, such as Random Forest in identifying factors underlying fire regime changes, GAM to describe the climate-human conditions relationship with fire regime features, or GWLR which enabled us to discover the spatial patterns of drivers. In turn, ARIMA models made it possible to project the temporal inertia of the main fire features into the near-future. Moreover, classification algorithms, such as KNN, were essential for replicating fire regime categories in both the past and future; and hierarchical clustering to optimize the fire regime typologies process. In addition, Mann Kendall and Sen's slope tests contributed to extracting the temporal evolution (sign and magnitude of the trend) of time series for the features time series in different stages of the dissertation.

On the other hand, it is necessary to be aware of some uncertainty in the fire phenomenon models as an analysis technique. For instance, working with averaged fire features or integrated in main components (PCA) may mask their variance. The Spanish fire database (EGIF), although it is one of the most extensive and complete in Europe, contains several changes of criteria in the way fire events were recorded over the years, which affects wildfire characterization. However, taking as a reference the concept of fire regimes, such as the mean conditions of fire features in a given area and time, this perspective was deemed more appropriate for the purposes of simpler and clearer interpretation.

Main conclusions

The specific conclusions according to the objectives (Chapter 2) are summarized below.

a) Explore the spatial-temporal distribution of fire regime features and their relation with climate-human factors:

- We have confirmed our hypothesis that, in mainland Spain, there are various fire regimes. The main fire features are fire frequency, burned area from large fires (>500 ha) and burnt area caused by lightning. The northwest region constitutes an example of human impact during winter, while seasonal variability in fire activity in the hinterland and Mediterranean has been mainly driven by weather conditions. Specifically, the northwest and hinterland regions exhibit high frequency of summer fires (including large fires), whereas during winter human-induced fires are more common. The Mediterranean region is best characterized by burned area features, and although fire frequency is important in summer, it takes second place in winter.

- Two main trends based on seasonality were detected: an increase in fire frequency during winter and a decrease in burnt area during summer. In both cases, human causality is strongly associated to fire tendencies and changes. At province or NUTS3 level, different behaviors are found in the northwest region (increasing in frequency and decreasing in burned area). On the other hand, change point detection found a common breakpoint in the late 1980s and in the first half of the 1990s. In turn, the Mann-Kendall test indicated that the Mediterranean showed the strongest negative tendencies, in contrast to the other regions. Finally, Sen's slope suggested wide spatial-seasonal variability and some trend gradients related to overall frequency and natural fires. Generally, the total number of fires depicts a rising trend (greater in winter) whereas there is an overall decline in burnt area.

b) Estimate the contribution of fire-weather danger on the temporal evolution of fire activity:

- Weather conditions control seasonal cycles of fire activity but have a limited influence on long-term trends. Fire danger is better related to fire frequency than burned area size; however, diverse spatial patterns are found, depending on the causality and final fire size. The seasonal influence of weather is most noticeable in the two months prior to the fire, although in the hinterland this influence stretches to three months. In the northwest region, seasonal burned area correlations are more associated with intentionality. The trend component of the Mediterranean has desynchronized with fire-weather danger since 1994, indicating the predominance of human factors. Finally, FWI and FFDI indices can be deemed useful for studying fire-weather associations at a regional level, while BI is significant at local level.

c) Analysis of spatial-temporal changes in the role of anthropogenic drivers on wildfires:

- GWR points out that some human drivers vary over time and are losing ground to climate factors, probably due to a successful fire prevention policy. Therefore, new explanatory factors should be taken into account (for example: arson variables or climate conditions). However, this temporal evolution is not stationary in space or time. In particular, both wildland interfaces and protected natural areas seem to be losing the power to explain the probability of fire ignition.

d) Characterize the dynamics of recent-future fire regimes and know the drivers of their changes:

- Five regime typologies are outlined at 10x10 km grid level (1) low fire activity, (2) medium-sized wildfires with a fair contribution from natural causes, (3) medium-sized forest fires with a high proportion of human-caused fires, (4) large wildfires with a significant presence of lightning, and (5) the high incidence of fire during winter. Overall, falling trajectories are most commonly found, covering an extensive area, although winter activity has progressed into the northwest and remains across the north. Demographic potential seems to be the main driver behind most transitions, followed by climatic tendencies. Wildland interfaces appear to be (WAI and WUI) directly associated with upward transitions (also winter progression) and inverse to downward ones.

- Four fire regime typologies were preserved at 30x30 km grid level (1) low fire activity, (2) medium-sized wildfires in summer with a small contribution from natural fires, (3), large fires caused by lightning, and (4) large fires related to winter activity. A reduction in fire activity is the most common scenario for the future, with a general increase in regions with a low incidence of fire.

e) Translating fire regime zoning schemes into pyroregions:

- Four large pyroregions have been outlined and characterized:

  (1) The **Northwest-Atlantic**, which concentrates the strongest winter progression of human-caused fires, and is driven by moderate-high wildland agricultural interface (WAI), an overall decline in demographic potential (DP), stable-increasing trends in climate variables in a region with diverse topography. The main sub-regions are **Atlantic Galicia** and the **Cantabrian Cornice**, both represented by the most noticeable winter progression of wildfires. The **León and Zamora** sub-region is also noteworthy for a minor increase in fire activity.

  (2) The **inner Mediterranean,** which shows major and minor decreases in fire activity; is influenced by low WAI in the Pyrenees but medium-high in the remaining territory; stable DP in northern flat areas, increases in Madrid and Murcia, decreases in the southern plateau; there are temperature increases in mountain areas; rainfall exhibits a decreasing-increasing gradient from north to south; medium-high elevation in flat areas with steep slopes in the east.

  (3) The **inland mountain ranges** combine winter fire progression and minor increases in fire activity; it is driven by medium WAI, low-medium WUI near Madrid; a falling to rising west-east gradient in DP; stable precipitation and increases in temperature; topographical gradients are also found. It must be pointed out that there are two regions with a moderate increase in forest fires (the area of the **Central System Range** and **northwest Extremadura**). There is also a region with a strong increase in winter fires in the **west of the Central System**.

  (4) The **Levante and southwest coast** have slightly reduced fire activity with some enclaves of minor rises in wildfires, it is influenced by a generalized medium-high WAI, low WUI (but with medium-high urban interface in Catalonia), stable-increasing DP, significant increases in climate drivers, and low-medium altitudes with rugged territory.

Future research

Although this PhD Thesis provides innovative insights into the identification and characterization of fire regimes, it is logical that there are many aspects which can be explored and improved by promoting further research. Although the spatial perspective has been assessed at three different levels (regional, provincial, grid) and the minimum official unit of reference (10x10 km) seems to be the most appropriate, it might be necessary to move towards a more detailed spatial unit, due to the finer resolution of explanatory variables which are currently available.

Many and innovative future research lines are opened in terms of a more profound characterization of the evolution of fire regimes. The temporal dimension has been addressed in detail; however, it is evident that future estimations entail high uncertainty. Therefore, specific proposals for future research are presented:

i. Deeper insights into causes explaining temporal behavior of the main fire regime features should be explored, especially those linked to changes in land use.
ii. Small fires (1 < ha) could be included, thus enriching fire regime assessment in order to avoid potential bias caused by their exclusion.
iii. Move towards fine tuning the existing fire-weather indices, depending on the environment analyzed.
iv. Further investigation into the temporal behavior of driving factors, taking into account seasonal variability in fire occurrence (divided into summer and winter).
v. Isolate the influence of large fires and analyze fire drivers separately in order to assess the degree of contribution of fire size.
vi. Consider taking into account fire features in several subsets (e.g. season, cause and size) in the context of fire modeling, as it helps to more clearly unravel the variability in the occurrence of fire.

Las metodologías empleadas en la presente tesis han perseguido cubrir los siguientes propósitos generales: a) determinar la distribución espacio-temporal de las métricas de incendio que mejor caracterizan al régimen general del fuego, b) evaluar la contribución del riesgo meteorológico en la evolución temporal de la actividad del fuego, c) analizar los cambios espacio-temporales de la influencia de los factores antrópicos en los incendios forestales causados por el hombre, d) describir y caracterizar la evolución y las casusas de los cambios en el régimen de incendios, y e) obtener una cartografía general de la piroregiones a partir de la zonificación del régimen de incendios.

Delimitar y caracterizar regiones homogéneas de régimen de incendios (piroregiones) constituye una tarea laboriosa y compleja que debe tener en cuenta diversos aspectos de los incendios forestales. En primer lugar, la selección de las características del fuego, paso importante debido que estas experimentan cambios espacio-temporales. En segundo lugar, conocer los factores dirigentes de los incendios involucrados en las trayectorias mostradas por los regímenes de incendio forestales.

La dimensión temporal de los regímenes de incendio ha sido la piedra angular de todas las etapas de la investigación. En este sentido, se ha demostrado que los regímenes de incendio no son estacionarios, mostrando tanto tendencias como una marcada estacionalidad en determinadas regiones de la España peninsular. Por lo tanto, esto ha facilitado la identificación de regiones con una mayor propensión a los incendios, que, en algunos casos, también han demostrado estar experimentando un alargamiento de la temporada estival de incendios.

Es importante destacar el alto potencial de los métodos empleados a lo largo de la investigación para caracterizar los regímenes de incendios. En particular, destacamos el rendimiento de la regresión multivariante: como *Random Forest* en la identificación de los factores que están detrás de los cambios en el régimen de incendios, GAM para describir la relación entre las condiciones climáticas-humanas y las métricas del régimen de incendios, o GWLR que nos permitió descubrir los patrones espaciales de los factores dirigentes. A su vez, los modelos ARIMA permitieron proyectar la inercia temporal de las principales métricas del fuego en el futuro cercano. Incluso los algoritmos de clasificación como KNN fueron esenciales para replicar las categorías de régimen de incendios hacia el pasado y el futuro, o el clúster jerárquico para optimizar el proceso de obtención de las tipologías de régimen de incendios. Además, las pruebas de Mann-Kendall y pendiente de Sen han contribuido a extraer la evolución temporal (signo y magnitud de la tendencia) de las series temporales de las métricas de incendio en diferentes etapas de la tesis.

Por otro lado, es necesario recordar la cierta incertidumbre de los modelos del fenómeno del fuego como técnica de análisis. Por ejemplo, trabajar con métricas de incendio promediadas o integradas en componentes principales (PCA) puede enmascarar en cierto grado su varianza. La base de datos de incendios española (EGIF), aunque es una de las más extensas y completas de Europa, contiene varios cambios de criterio en la forma en que se registran los sucesos de incendios a lo largo de los años, lo que afecta a la caracterización de los incendios forestales. Sin embargo, tomando como referencia el concepto de regímenes de incendios, como las condiciones promedias de las características del fuego en una zona y momento determinados, esta perspectiva se ha considerado más apropiada a efectos de una interpretación más simple y clara.

Conclusiones principales

A continuación, se resumen las conclusiones específicas según los objetivos presentados en el Capítulo 2.

a) Explorar la distribución espacio-temporal de las métricas del régimen de incendios y su relación con las factores climáticos-humanos:

- Hemos confirmado nuestra hipótesis de que las tres regiones tradicionales de la España peninsular tienen regímenes de incendio diferentes. Las principales métricas de incendio son: la frecuencia de incendios, el área quemada por grandes incendios (> 500 ha) y el área quemada por causa de rayos. La región Noroeste representa un ejemplo claro del impacto humano durante el invierno, mientras que la variabilidad estacional en el interior y el Mediterráneo ha sido impulsada principalmente por las condiciones climáticas. Concretamente, las regiones del Noroeste y del Interior muestran una alta frecuencia de incendios en verano (incluidos los grandes incendios), mientras que durante el invierno los incendios humanos desempeñan un papel más notable. La región mediterránea está mejor caracterizada por las métricas del área quemada, y aunque la frecuencia de incendios es relevante durante el verano, ocupa el segundo lugar en invierno.

- Se han detectado dos tendencias principales basadas en la estacionalidad: aumento de la frecuencia de incendios durante el invierno y el descenso del área quemada durante el verano. En ambos casos, la causalidad humana está fuertemente asociada a las tendencias y cambios de los incendios. A nivel provincial o NUTS3 se encuentran diferentes comportamientos en la región noroeste (aumento de la frecuencia y disminución de la superficie quemada). Por otra parte, la detección de puntos de cambio ha encontrado un punto de ruptura común a finales de la década de 1980 y en la primera mitad de la década de 1990. El test de Mann-Kendall reveló que el Mediterráneo presenta las mayores tendencias negativas, en contraste con el resto de regiones. Finalmente, la pendiente de Sen sugirió una gran variabilidad espacio-temporal y algunos gradientes de tendencia relacionados con la frecuencia general y los incendios naturales. En general, el número total de incendios representa un aumento (mayor en invierno), mientras que el área quemada experimenta una disminución general.

b) Estimar la contribución del riesgo de incendio meteorológico en la evolución temporal de la actividad de los incendios:

- Las condiciones climáticas controlan los ciclos estacionales de la actividad del fuego, pero tienen una influencia limitada en las tendencias a largo plazo. El riesgo de incendio está más relacionado con la frecuencia de incendios que con el tamaño del área quemada, sin embargo, se encuentran diversos patrones espaciales dependiendo de la causalidad y el tamaño final del incendio. La influencia estacional del clima es más notable en los dos meses anteriores al incendio, aunque en el interior esta influencia alcanza significativamente los tres meses. Para el caso de la región Noroeste, las correlaciones estacionales de áreas quemadas están más asociadas a la intencionalidad. En cuanto al componente de tendencia del Mediterráneo, muestra una desincronización con el peligro de incendios desde 1994, revelando la supremacía de los factores humanos. Por último, los índices de FWI y FFDI pueden considerarse útiles para el estudio de las asociaciones de entre incendios y meteorología a nivel regional, mientras que el índice BI destaca a nivel local.

c) Análisis de los cambios espacio-temporales en el peso de los factores antropogénicos en los incendios forestales:

- GWR señala que algunos factores humanos varían con el tiempo y están perdiendo protagonismo dando paso a los factores climáticos, probablemente debido a una exitosa política de prevención de incendios. Por lo tanto, deberán tenerse en cuenta nuevos factores explicativos (por ejemplo: variables relacionadas con incendios provocado o condiciones climáticas). Sin embargo, esta evolución temporal no es estacionaria ni en el espacio ni en el tiempo. En particular, tanto las interfaces forestales como las áreas naturales protegidas parecen estar perdiendo poder explicativo en términos de la probabilidad de ignición del fuego.

d) Caracterizar la dinámica de los regímenes de incendios recientes-futuros y conocer las causas de sus cambios:

- Se han esbozado cinco tipologías de régimen de incendios a nivel de cuadrícula de 10x10 km (1) baja actividad de incendios, (2) incendios forestales de tamaño medio con una contribución justa de causa natural, (3) incendios forestales de tamaño medio con un alto peso de incendios de origen humano, (4) incendios forestales de gran tamaño con una presencia notable de los causados por rayo, y (5) la alta incidencia de incendios durante el invierno. En general, las trayectorias de descenso son la situación más común, cubriendo un territorio extenso. Aunque, la actividad invernal ha progresado hacia el noroeste y persiste a lo largo del norte. El potencial demográfico parece ser el principal impulsor de la mayoría de las transiciones, seguido de las tendencias climáticas. Las interfaces forestales (WAI y WUI) aparecen asociadas directamente a transiciones ascendentes (también progresión invernal) e inversamente a tendencias descendentes.

- Asimismo, se han conservado cuatro tipologías de régimen de incendios a nivel de cuadrícula de 30x30 km: (1) baja actividad de incendios, (2) incendios forestales de tamaño medio en verano con baja contribución de incendios naturales, (3) incendios de gran superficie relacionados con los rayos, y (4) grandes incendios relacionados con la actividad invernal. La disminución de la actividad de los incendios es la situación más común hacia el futuro inmediato, con un aumento general de las regiones con baja incidencia de incendios.

e) Trasladar los esquemas de zonificación del régimen de incendios en piroregiones:

- Se han trazado y caracterizado cuatro grandes piroregiones:

(1) El **noroeste Atlántico**, que concentra la mayor progresión invernal de los incendios provocados por el hombre, y está impulsado por una interfaz agrícola forestal moderada y alta (WAI), una disminución general del potencial demográfico (DP) y tendencias estables en aumento de las variables climáticas en un territorio de topografía diversa. Las principales subregiones son la **Galicia Atlántica** y la **Cornisa Cantábrica**, ambas representadas por la más notable progresión invernal de los incendios forestales. Destaca también la subregión de **León y Zamora**, que se caracteriza por un leve aumento de la actividad de incendios.

(2) El **Mediterráneo interior**, que presenta disminuciones mayores y menores de la actividad de los incendios; está influenciado por un WAI bajo en los Pirineos pero medio-alto en el resto del

territorio; DP estable en las zonas llanas del norte, aunque con aumentos en Madrid y Murcia, así como disminuciones en la meseta sur; la temperatura muestra aumentos en las zonas montañosas y las precipitaciones presentan un gradiente decreciente que aumenta de norte a sur. Por último, la elevación es media-alta con zonas llanas y pendientes pronunciadas en el este.

(3) Las **cordilleras interiores** combinan la progresión invernal del fuego con pequeños incrementos de la actividad del fuego; está impulsada por un WAI medio-bajo, WUI medio cercano a Madrid; DP presenta un gradiente oeste-este de decrecimiento a aumento; estabilidad en la precipitación y aumentos de temperatura; existen gradientes topográficos. Cabe destacar dos subregiones con un aumento moderado de los incendios forestales (entorno del **Sistema Central** y el **Noroeste de Extremadura**), pero también encontramos una región con un marcado aumento de los incendios invernales en el **oeste del Sistema Central**.

(4) El **"Levante" y la costa suroeste** destaca por una ligera disminución de la actividad de los incendios con algunos enclaves de pequeños incrementos en los incendios forestales, está influenciado por una generalizada WAI media-alta, una WUI baja (pero con una interfaz urbana media-alta en Cataluña), una DP estable y creciente, incrementos significativos en los generadores de cambio climático, en las altitudes medias-bajas y en el territorio escarpado.

Futuras investigaciones

Aunque esta tesis proporciona nuevas perspectivas sobre la identificación y caracterización de los regímenes de fuego, es lógico que existan muchos aspectos en los que profundizar y mejorar, promoviendo otras investigaciones futuras. Aunque el aspecto espacial se ha evaluado en tres niveles diferentes (regional, provincial, cuadrícula) y la unidad mínima oficial de referencia (10x10 km) parece ser la más adecuada, podría ser necesario avanzar hacia una unidad espacial más detallada, debido a la mayor resolución de las variables explicativas actualmente disponibles.

Se abren muchas e innovadoras líneas de investigación futuras en términos de una caracterización más profunda de la evolución de los regímenes de incendios. La dimensión temporal ha sido abordada en detalle, sin embargo, es evidente que en la estimación futura se asume una alta incertidumbre. Por lo tanto, se presentan algunas propuestas específicas de investigación:

i. Se debe ir una comprensión más profunda de las causas que explican el comportamiento temporal de las principales métricas del régimen de incendios, especialmente las relacionadas con los cambios en el uso del suelo.
ii. Podrían incluirse los conatos (1 < ha), lo que enriquecería la evaluación del régimen de incendios para evitar los posibles sesgos causados por su exclusión.
iii. Avanzar hacia una puesta a punto de los índices meteorológicos existentes, en función del entorno analizado.
iv. Se podría desarrollar una investigación más detallada sobre el comportamiento temporal de los factores impulsores, teniendo en cuenta la variabilidad estacional de la ocurrencia de incendios (dividida en verano e invierno).
v. Aislar la influencia de los grandes incendios y analizar por separado los factores dirigentes de incendios para evaluar el grado de contribución del tamaño del fuego.

vi. Considerar la posibilidad de tener en cuenta las características del fuego en agregados en varios subconjuntos (por ejemplo, por estación, causa y tamaño) en el contexto de la modelización de incendios, ya que ayuda a desentrañar con mayor claridad la variabilidad del fenómeno del fuego.

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A

APPENDIX A: SUPLEMENTARY MATERIAL OF FIRE REGIME FEATURES

This appendix presents the supplementary material of the paper entitled "*Understanding wildfires in mainland Spain. A comprehensive analysis of fire regime features in a climate-human context*" which shows complementary results obtained in this publication.

SUPPORTING INFORMATION

Understanding wildfires in mainland Spain. A comprehensive analysis of fire regime features in a climate-human context

Adrián Jiménez-Ruano, Marcos Rodrigues Mimbrero, Juan de la Riva Fernández

Appendix 1 Supplementary maps

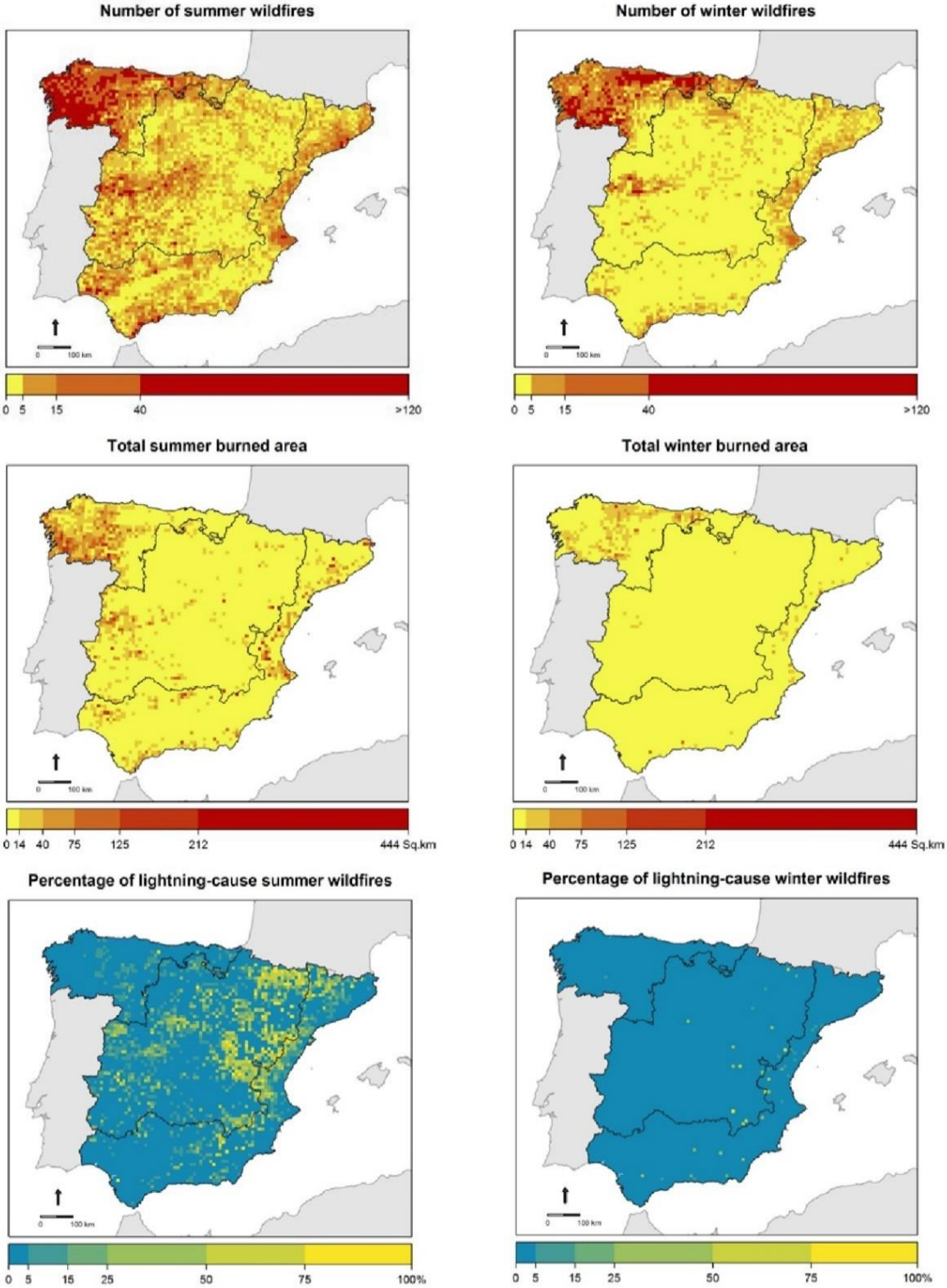

Figure A1. Fire features by season of the entire study area. Note that the scale in the map for each variable is adjusted to its own range to maximize the visualization of spatial variation

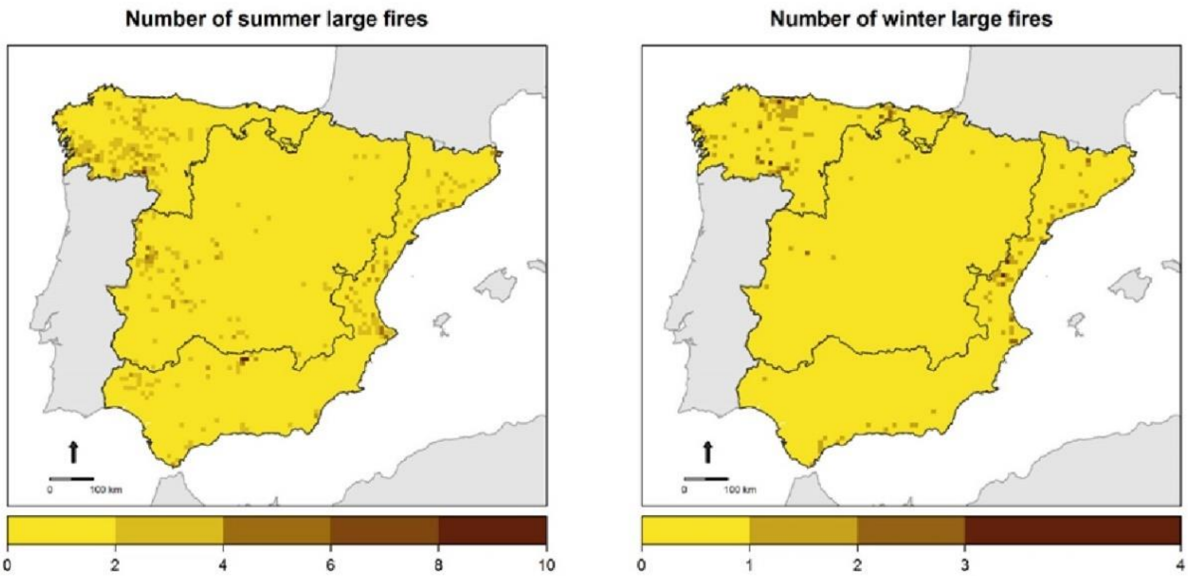

Figure A1. Fire features by season of the entire study area. (Continued)

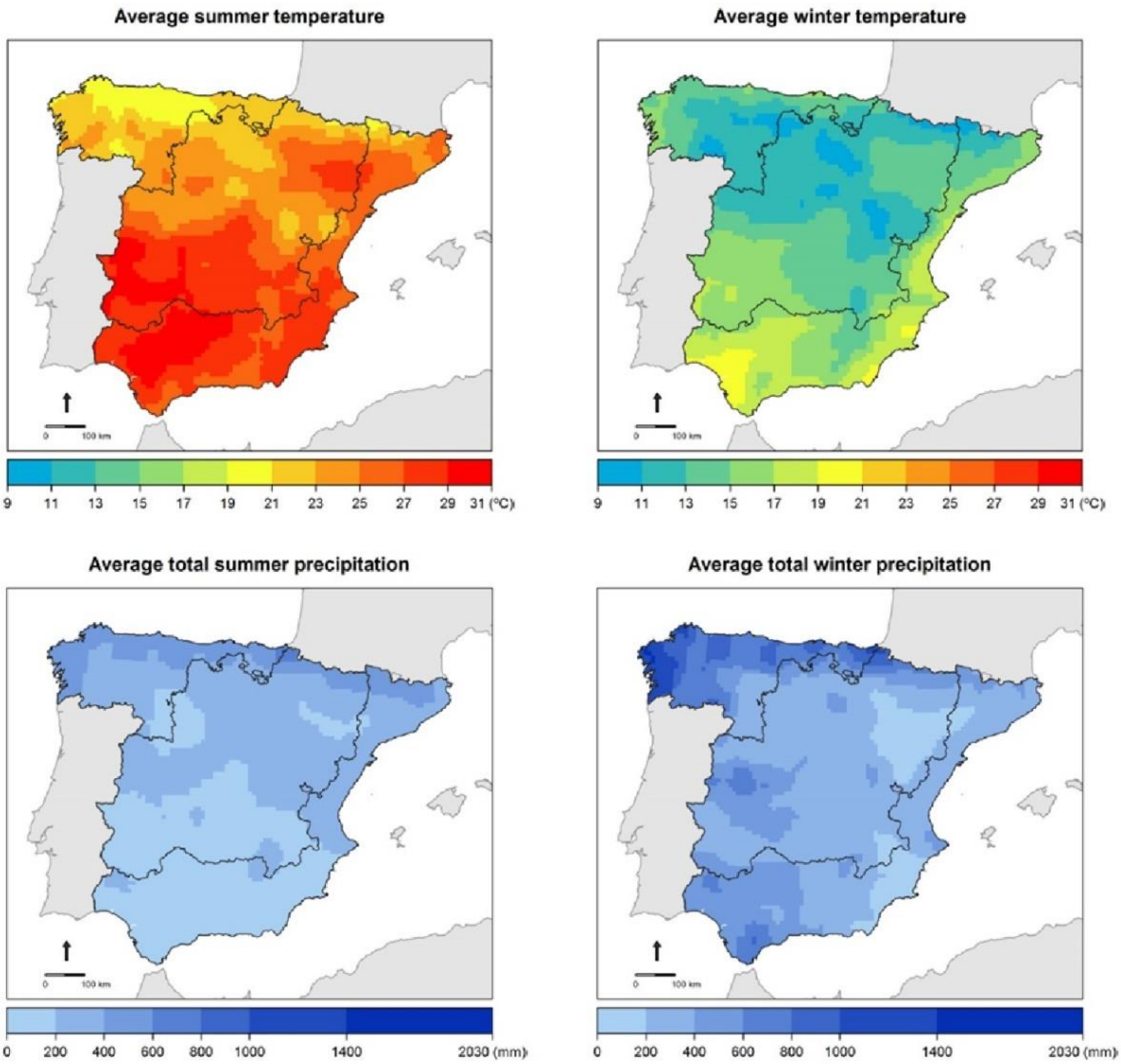

Figure A2. Climatic characterization of the mainland Spain average maximum temperature and average total precipitation by season (summer and winter)

Appendix 2 Supplementary tables

Table A1. Values and ranges of climatic variables in each region and season. Both variables, temperature and precipitation, were reclassified in ten equal groups.

Region	Temperature reclassified	Temperature average values (ºC)	Precipitation reclassified	Total precipitation average values (mm)
Northwest summer	*1*	19 – 19.61	*1*	169.75 – 227
	2	19.62 – 20.23	*2*	228 – 284.67
	3	20.24 – 20.84	*3*	284.68 – 342.08
	4	20.85 – 21.50	*4*	342.09 – 398.26
	5	21.51 – 22.13	*5*	398.27 – 455.34
	6	22.14 – 22.77	*6*	455.35 – 512.09
	7	22.78 – 23.39	*7*	512.10 – 569.14
	8	23.40 – 24.04	*8*	569.15 – 626,19
	9	24.05 – 24.68	*9*	626.2 – 683.24
	10	24.69 – 25.3	*10*	683.25 – 740.29
Northwest winter	*1*	9.37 – 10	*1*	227.61 – 348.27
	2	10.01 – 10.63	*2*	348.28 – 468,94
	3	10.64 – 11.29	*3*	468.95 – 589.61
	4	11.3 – 11.94	*4*	589.62 – 710.3
	5	11.95 – 12.61	*5*	710.4 – 831
	6	12.62 – 13.26	*6*	831.1 – 951.76
	7	13.27 – 13.94	*7*	951.77 – 1,072.4
	8	13.95 – 14.58	*8*	1,072.5 – 1,193.1
	9	14.59 – 15.24	*9*	1,193.2 – 1,313.8
	10	15.25 – 15.88	*10*	1,313.9 – 1,434.75
Hinterland summer	*1*	20.2 – 21.1	*1*	140.11 – 196.79
	2	21.11 – 22.1	*2*	196.8 – 253.48
	3	22.11 – 23.1	*3*	253.49 – 310.17
	4	23.11 – 24.1	*4*	310.18 – 366.86
	5	24.11 - 25.1	*5*	366.87 – 423.55
	6	25.11 – 26.1	*6*	423.56 – 480.24
	7	26.11 – 27.11	*7*	480.25 – 536.93
	8	27.12 – 28.11	*8*	536.94 – 593,62
	9	28.112 – 29.11	*9*	593.63 – 650,31
	10	29.12 – 30.11	*10*	650.32 - 707
Hinterland winter	*1*	9.69 – 10.48	*1*	152.24 – 242.04
	2	10.49 – 11.3	*2*	242.05 – 331.86
	3	11.31 – 12.116	*3*	331.87 – 421.68
	4	12.12 – 12.92	*4*	421.69 – 511.5
	5	12.94 – 13.74	*5*	511.51 – 601,32
	6	13.75 – 14.56	*6*	602.33 – 692.14
	7	14.57 – 15.379	*7*	692.15 – 781,96
	8	15.38 – 16.19	*8*	781.97 – 871,78
	9	16.20 – 17	*9*	871.79 – 961.6
	10	17.01 – 17.8	*10*	961.7 – 1,051.51
Mediterranean summer	*1*	19.35 – 20.49	*1*	72.15 – 123.59
	2	20.5 – 21.64	*2*	123.6 – 174.97
	3	21.65 – 22.79	*3*	174.98 – 226.42
	4	22.8 – 23.94	*4*	226.43 – 277.87
	5	23.95 – 25.15	*5*	277.88 – 329.32
	6	25.16 – 26.3	*6*	329.33 – 380.77
	7	26.31 – 27.46	*7*	380.78 – 432,22
	8	27.47 – 28.64	*8*	432.23 – 483.77
	9	28.65 – 29.79	*9*	483.78 – 535,22
	10	29.8 – 30.94	*10*	535.23 – 586.67
Mediterranean winter	*1*	9.3 – 10.34	*1*	163.04 – 226.84
	2	10.35 - 11.35	*2*	226.85 – 290.68
	3	11.36 – 12.36	*3*	290.69 – 354.52
	4	12.37 – 13.48	*4*	354.53 – 418.36
	5	13.49 – 14.53	*5*	418.37 – 482,2
	6	14.54 – 15.6	*6*	482.21 – 546.01
	7	15.61 – 16.66	*7*	546.02 – 609.85
	8	16.67 – 17.73	*8*	609.86 – 673.69
	9	17.734 – 18.79	*9*	673.7 – 737.5
	10	18.8 - 19.84	*10*	737.6 - 801.4

Appendix 3 Supplementary graphs

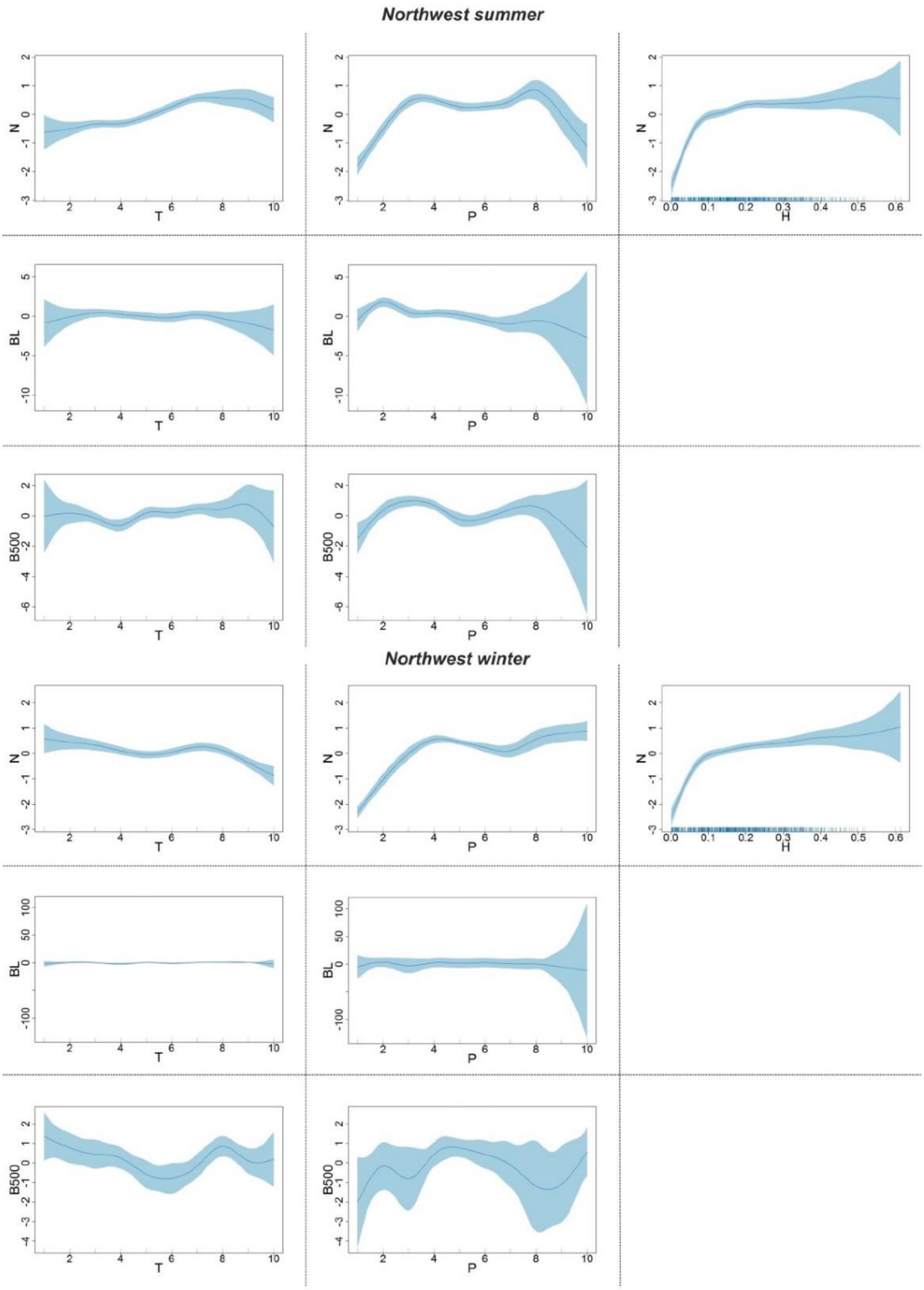

Figure A3. Estimated partial effects of number of fires (N), burned area of natural fires (BL) and burned area of large fires (B500) (solid line) with 95% confidence bands (shaded area) in the Northwest region (NW) and both seasons (spring-summer on first three rows on the top, autumn-winter on the last three rows on the bottom) for temperature (T) first column on the left, precipitation (P) second column in the center and human pressure (H) third column on the right.

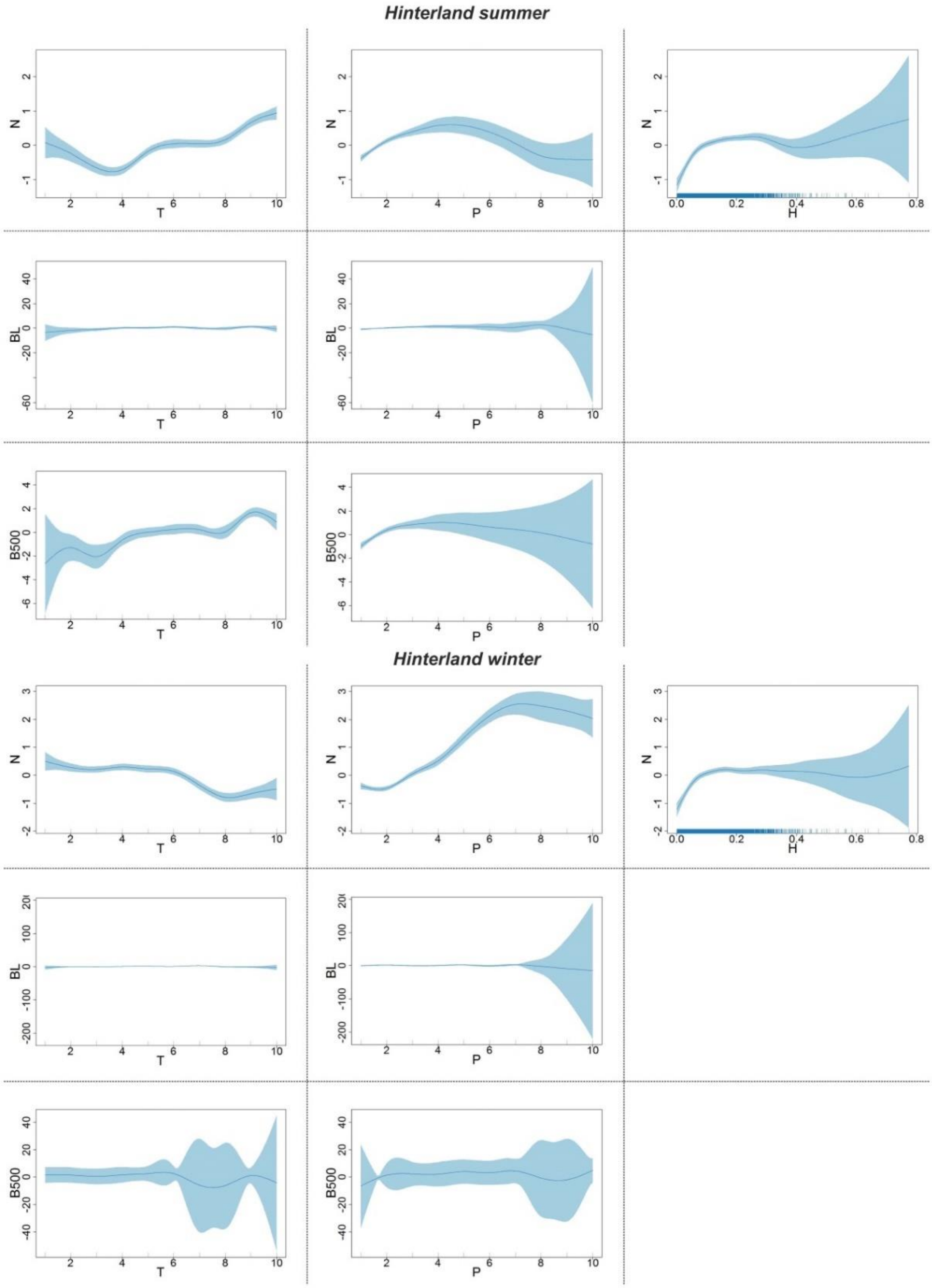

Figure A4. Estimated partial effects of number of fires (N), burned area of natural fires (BL) and burned area of large fires (B500) (solid line) with 95% confidence bands (shaded area) in the Hinterland region (HL) and both seasons (spring-summer on first three rows on the top, autumn-winter on the last three rows on the bottom) for temperature (T) first column on the left, precipitation (P) second column in the center and human pressure (H) third column on the right.

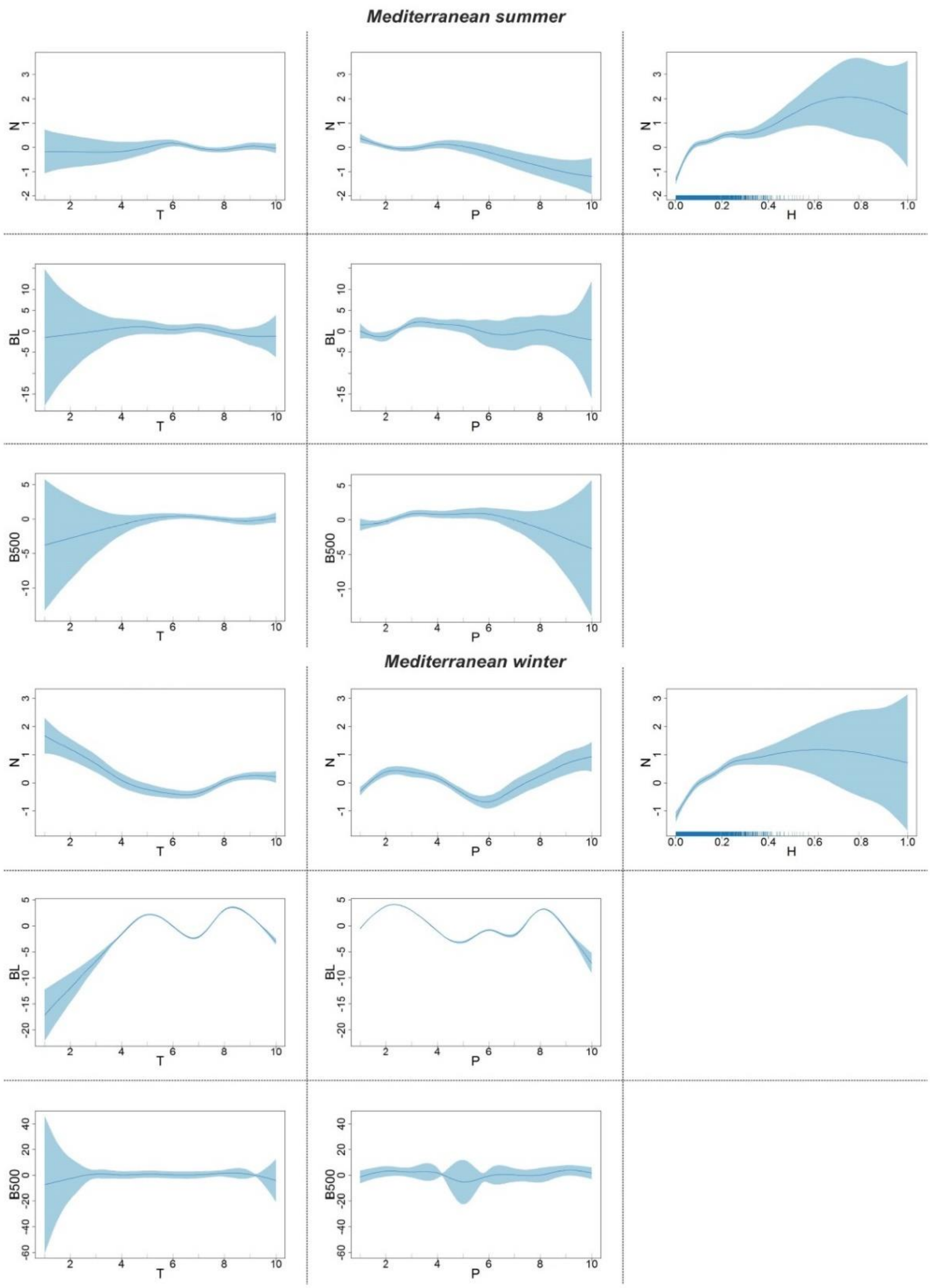

Figure A5. Estimated partial effects of number of fires (N), burned area of natural fires (BL) and burned area of large fires (B500) (solid line) with 95% confidence bands (shaded area) in the Mediterranean region (MED) and both seasons (spring-summer on first three rows on the top, autumn-winter on the last three rows on the bottom) for temperature (T) first column on the left, precipitation (P) second column in the center and human pressure (H) third column on the right.

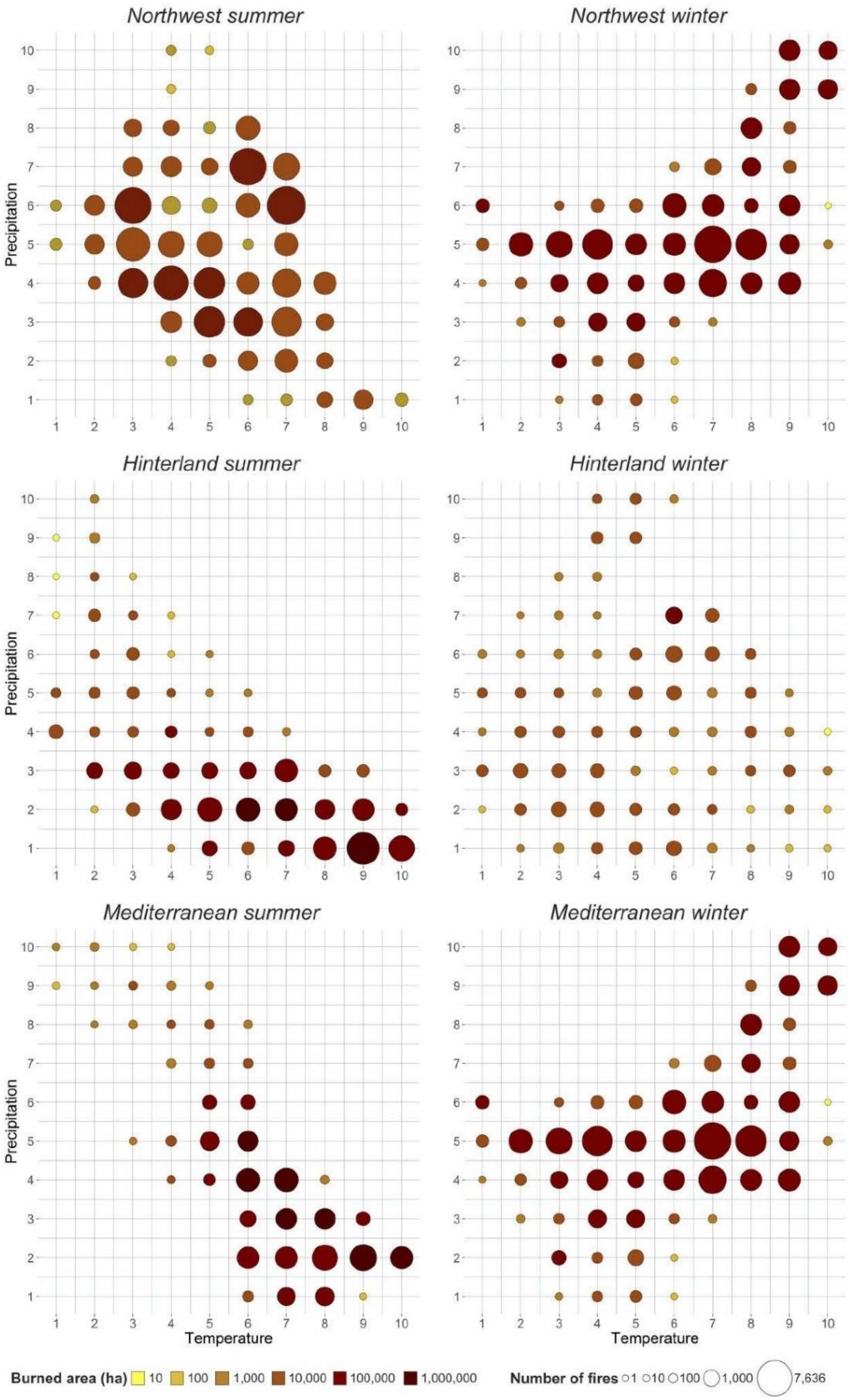

Figure A6. Multidimensional scatterplots for total burned area. Note values are given on the logarithmic scale.

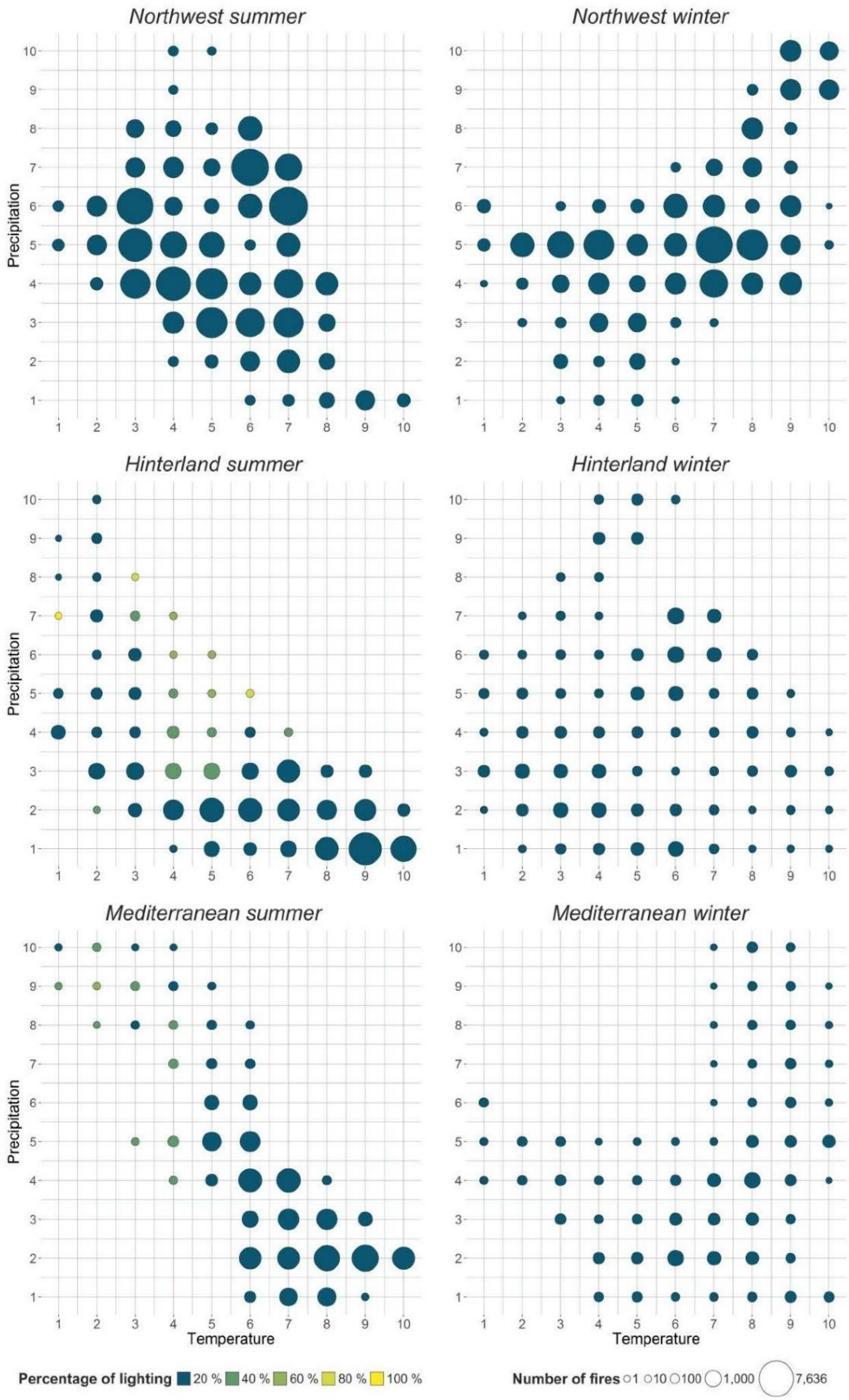

Figure A7. Multidimensional scatterplots for percentage of lightning.

B

APPENDIX B: SUPLEMENTARY MATERIAL OF FIRE-WEATHER

This appendix presents the supplementary material of the paper entitled "*The role of short-term weather conditions in temporal dynamics of fire regime features in mainland Spain*" which shows complementary results obtained in this publication.

SUPPLEMENTARY MATERIAL

The role of short-term weather conditions in temporal dynamics of fire regime features in mainland Spain

Adrián Jiménez-Ruano, Marcos Rodrigues Mimbrero, W. Matt Jolly and Juan de la Riva Fernández

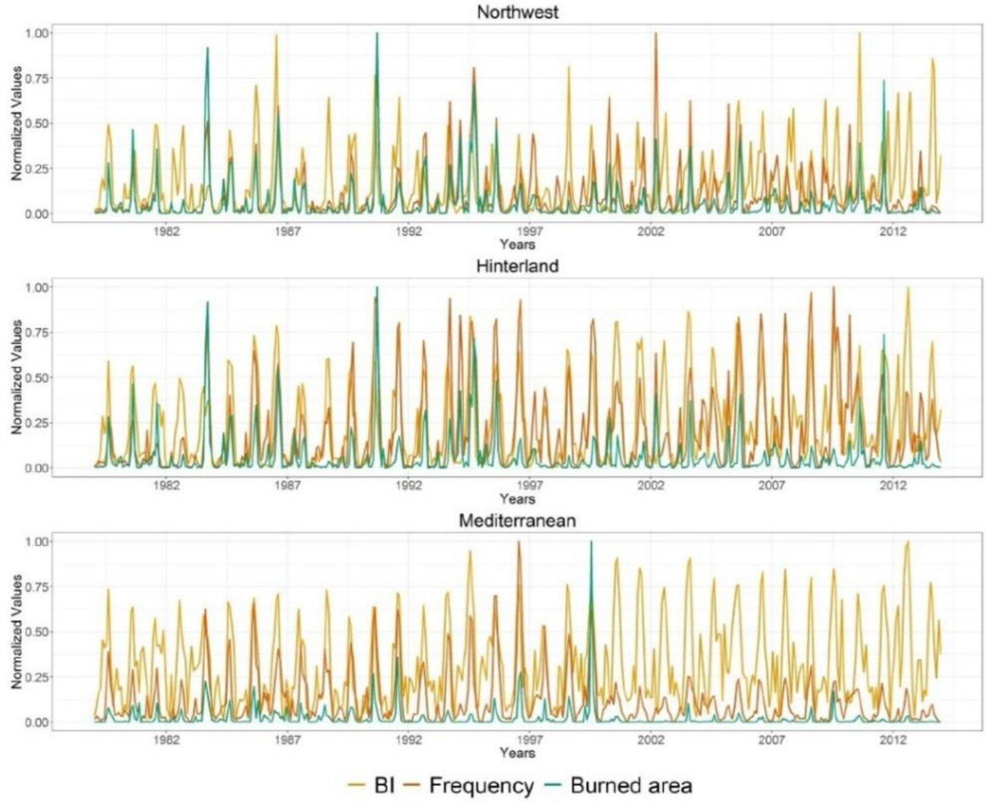

Figure S1. Time series of BI (yellow line), fire frequency (red line) and burned area (green line). All variables are normalized into a 0-1 range.

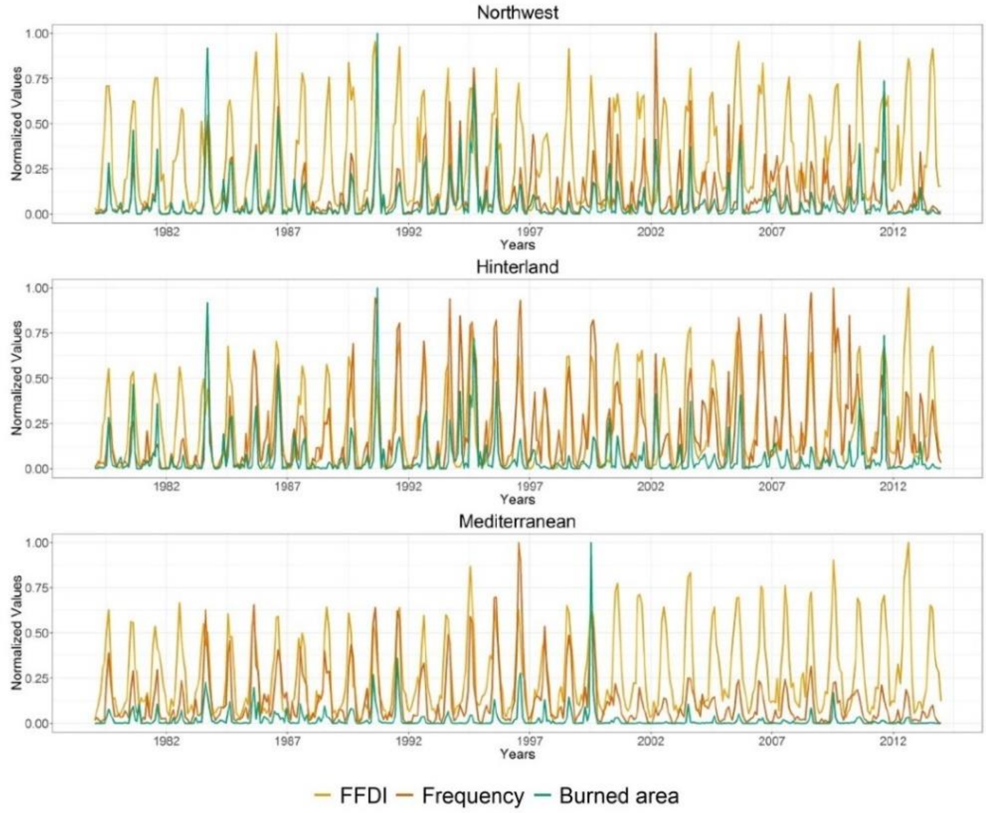

Figure S2. Time series of FFDI (yellow line), fire frequency (red line) and burned area (green line). All variables are normalized into a 0-1 range.

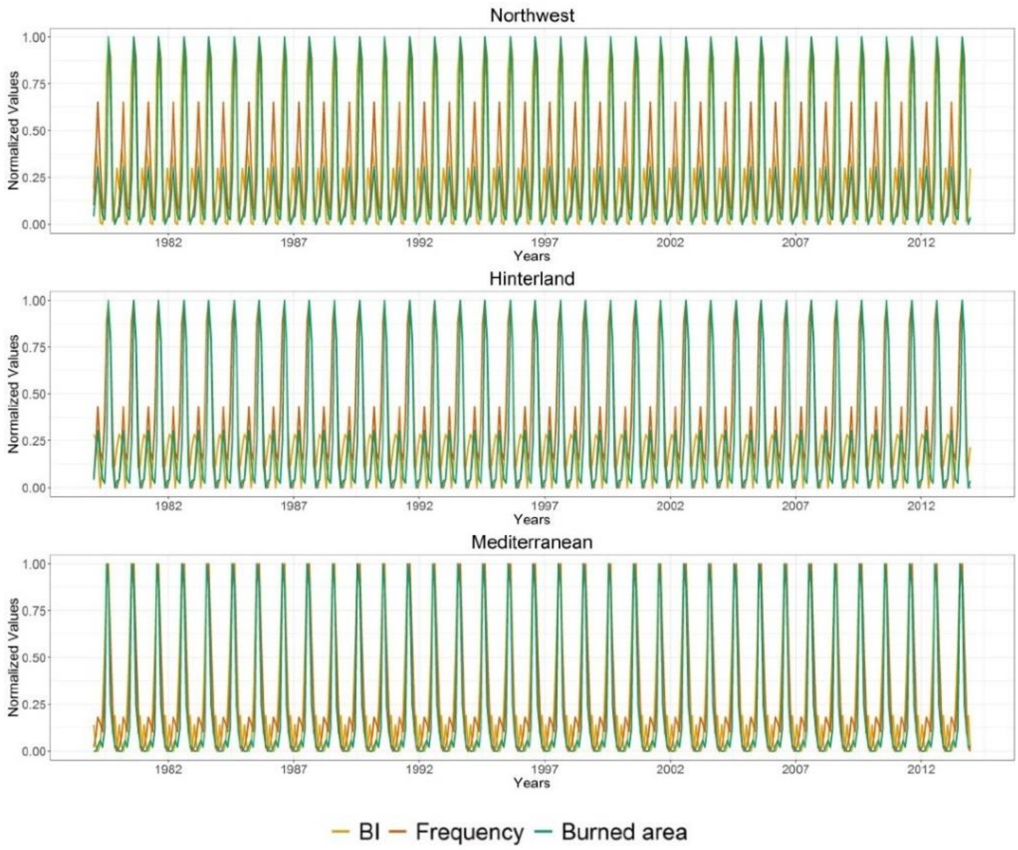

Figure S3 Time series of seasonal component of BI (yellow line), fire frequency (red line) and burned area (green line). All variables are normalized into a 0-1 range.

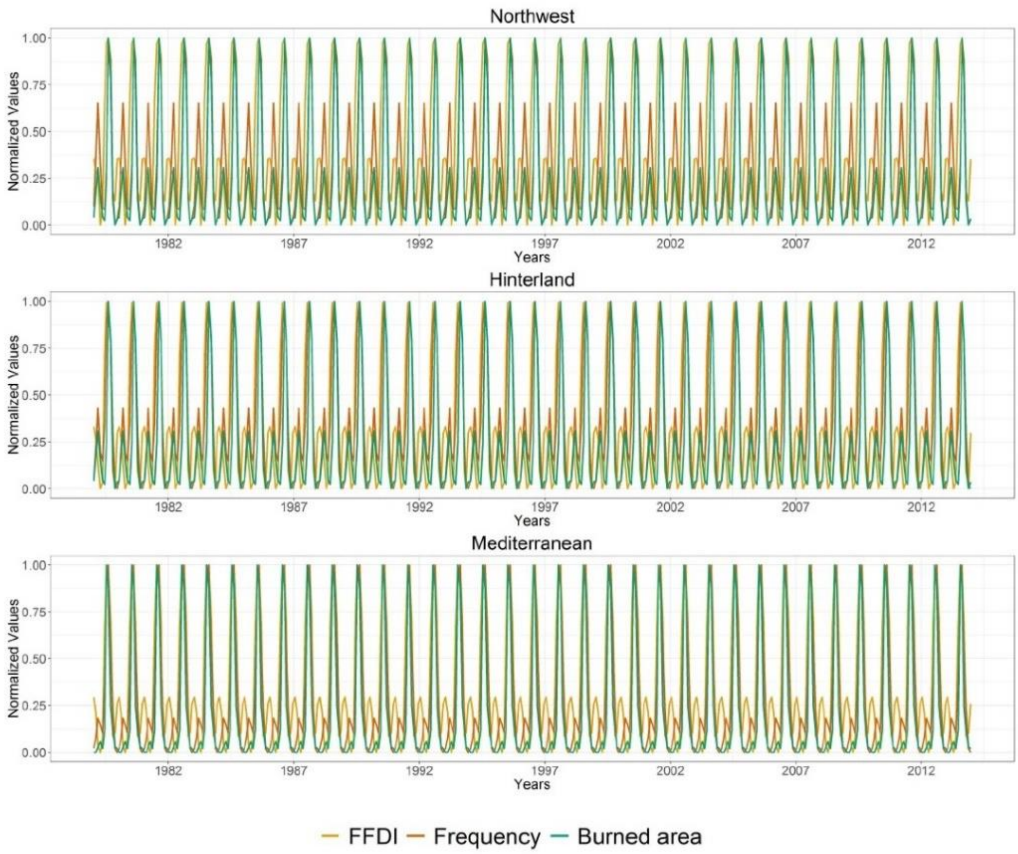

Figure S4. Time series of seasonal component of FFDI (yellow line), fire frequency (red line) and burned area (green line). All variables are normalized into a 0-1 range.

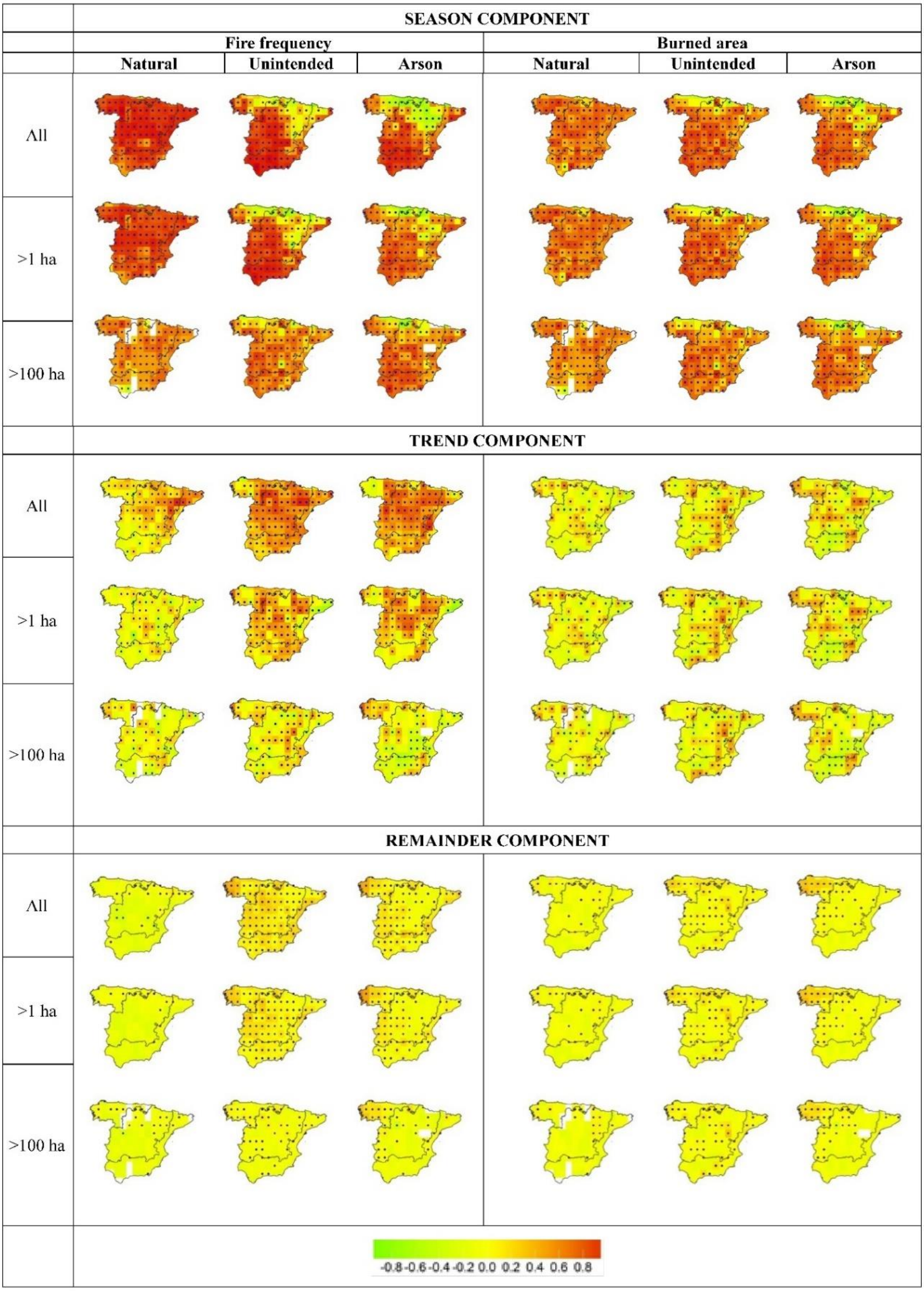

Figure S7. Spatial pattern of Pearson coefficients between FWI *vs*. seasonal, trend and remainder components of fire frequency (left) and burned area (right). Green to yellow values indicate negative association; yellow to red indicate positive association. Points mark significant relationships (p<0.05). Blank pixels indicate no-fire activity in the subset.

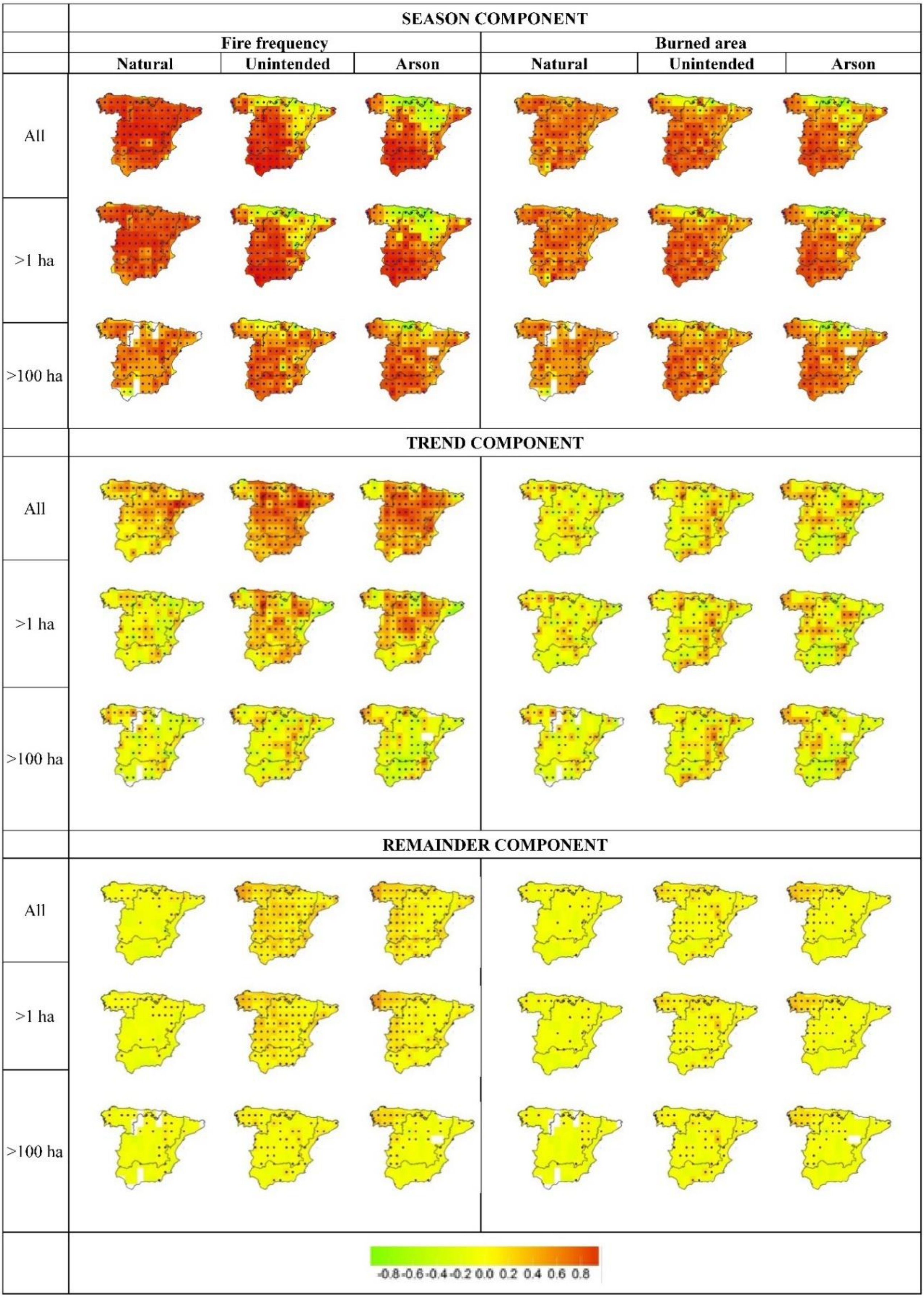

Figure S8. Spatial pattern of Pearson coefficients between seasonality, trend and remainder components of fire frequency-burned area vs. FFDI. Green to red gradient indicates relationships from negative to positive. Points indicate significant relationships for p value <0.05. Blank pixels indicate no contribution to the scenario.

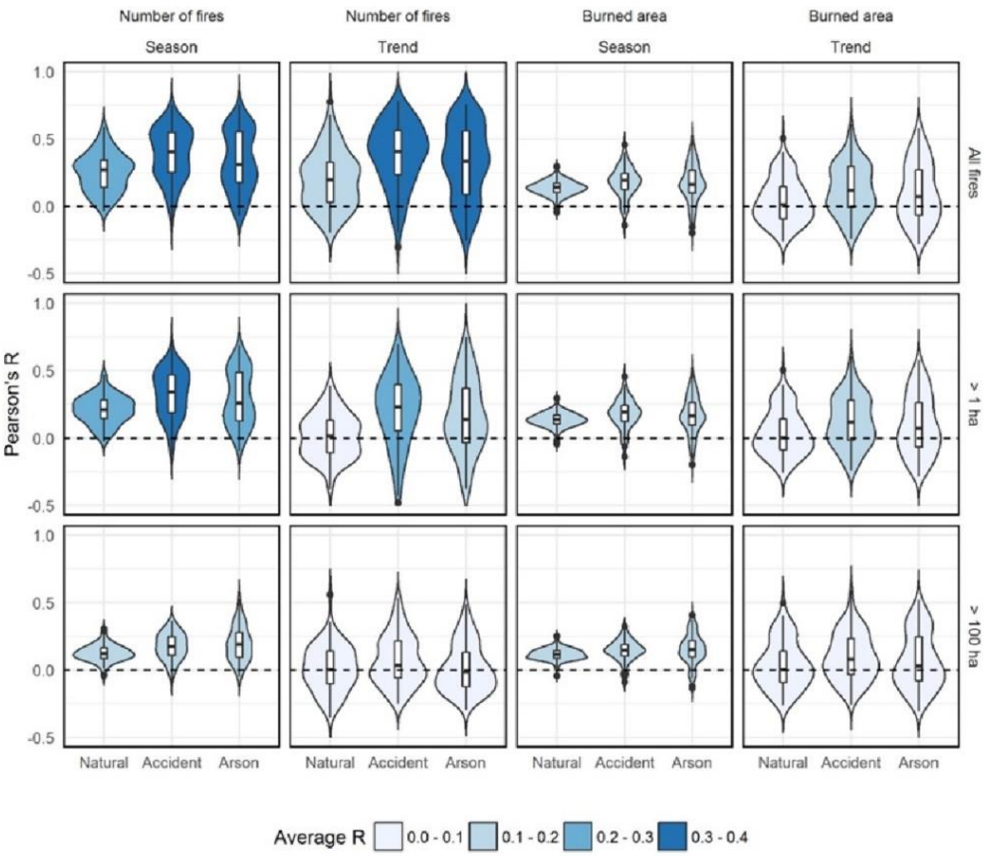

Figure S9. Statistical distribution of the Pearson's R between total number of fires-burned area and FWI. Blue gradient categories show the average of Pearson's R of pixels in each fire size-cause subset and component (season and trend).

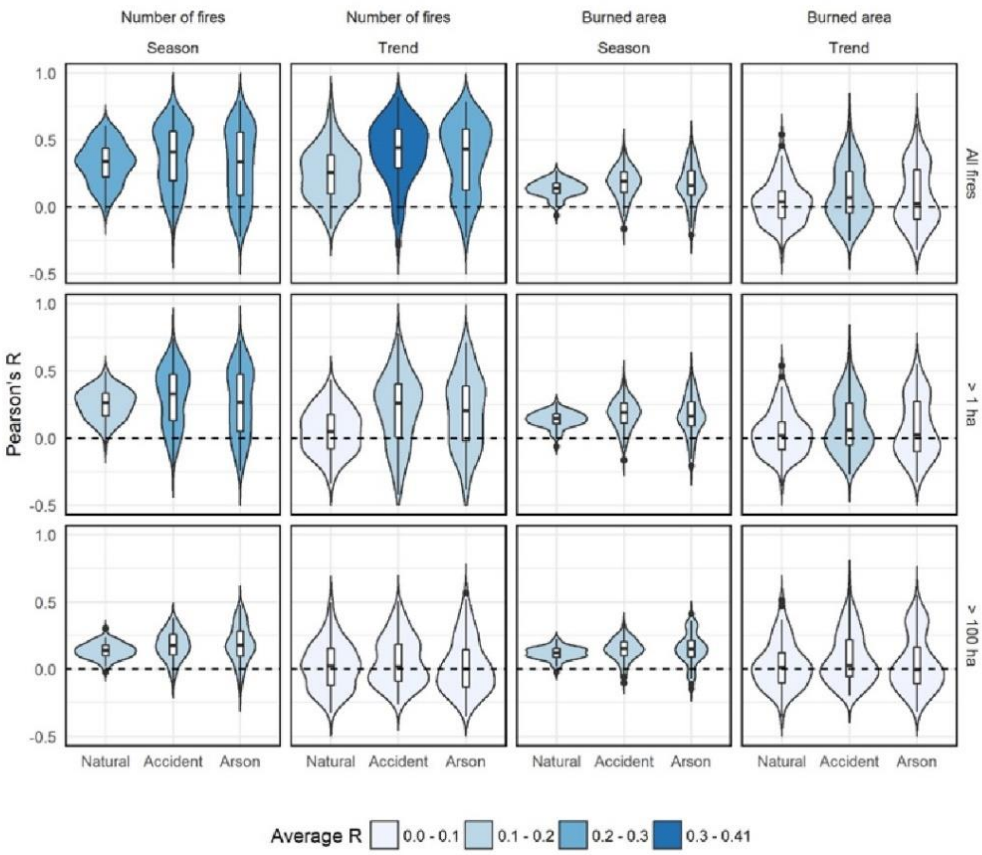

Figure S10. Statistical distribution of the Pearson's R between total number of fires-burned area and FFDI. Blue gradient categories show the average of Pearson's R of pixels in each fire size-cause subset and component (season and trend).

C

APPENDIX C: SUPLEMANTARY MATERIAL OF DRIVERS OF CHANGE

This appendix presents the supplementary material of the accepted paper entitled "Fire regime dynamics in mainland Spain. Part 1: drivers of change" which shows complementary results obtained in this publication.

Supplementary Material

Fire regime dynamics in mainland Spain. Part 1: drivers of change

Marcos Rodrigues, Adrián Jiménez-Ruano, Juan de la Riva Fernández

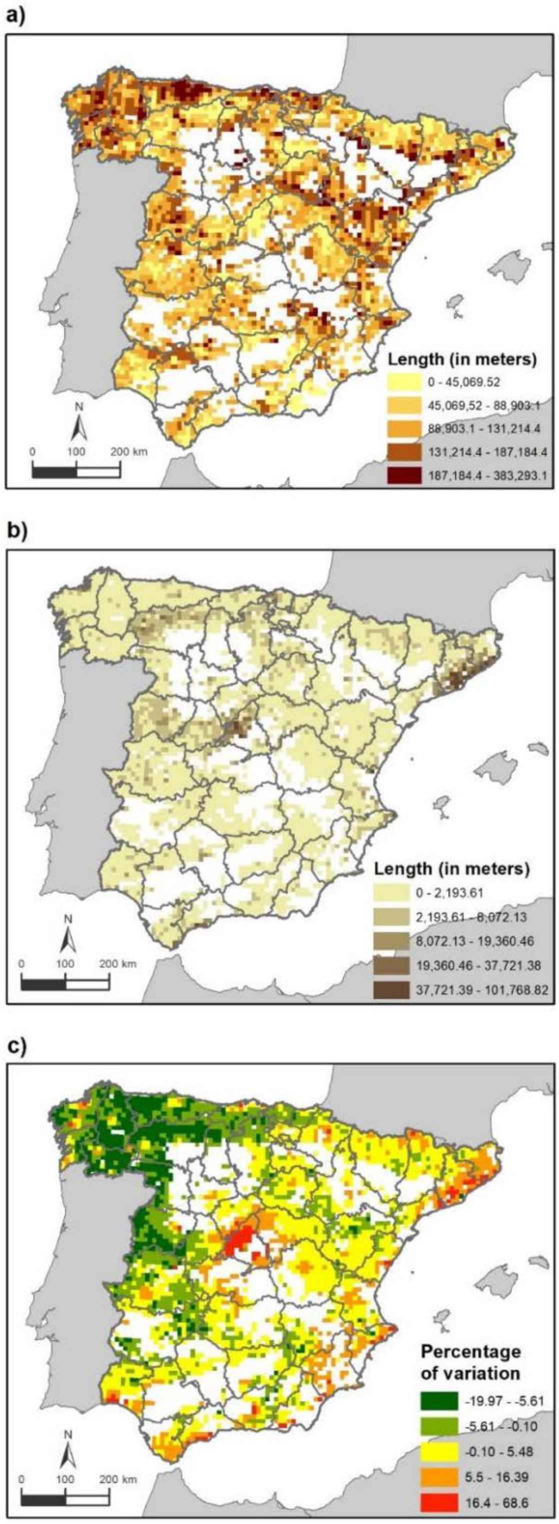

Fig. A1. Spatial distribution of the human related variables: **a)** WAI, **b)** WUI and **c)** Percentage of variation of demographic potential.

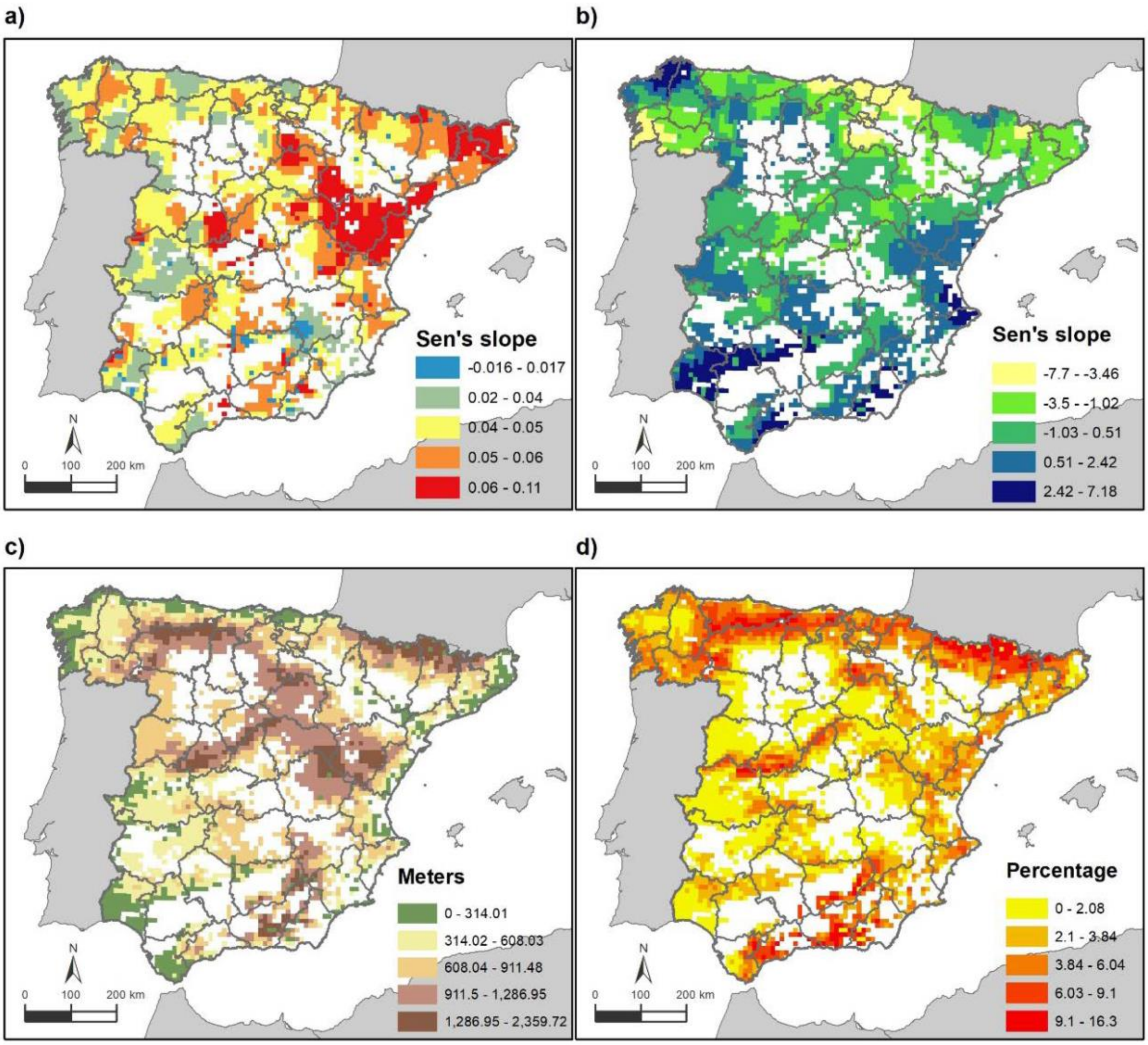

Fig. A2. Spatial distribution of the climate: **a)** Temperature trend, **b)** Precipitation trend; and topography variables: **c)** Elevation and **d)** Slope.

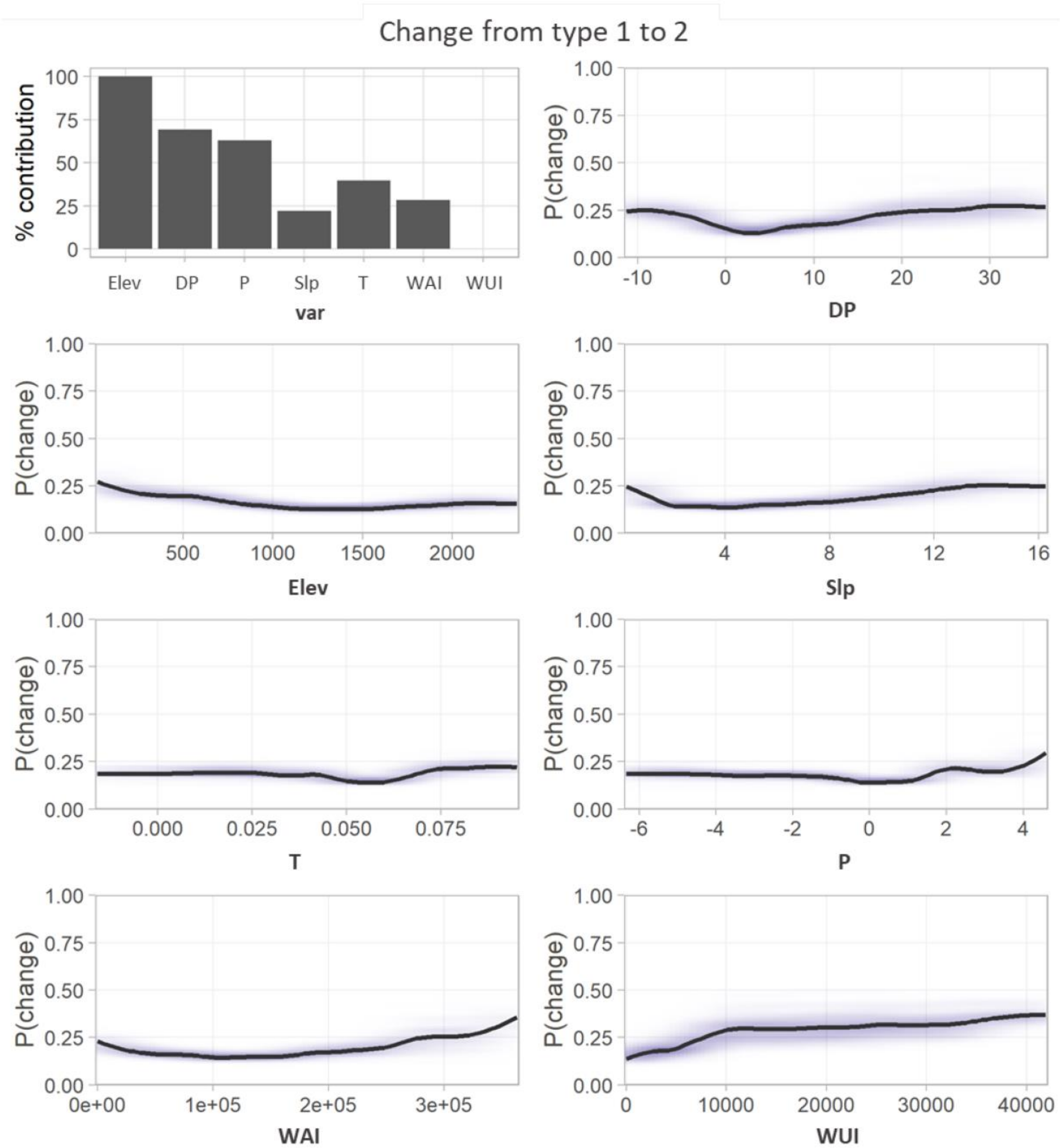

Fig. B1. Overall fire driver's contribution and the percentage of change for each explanatory variable in the fire regime transition **from type 1 to 2**. Elev: Elevation, DP: Demographic potential, P: Precipitation, Slp: Slope, T: Temperature, WAI: Wildland Agricultural Interface, WUI: Wildland Urban Interface.

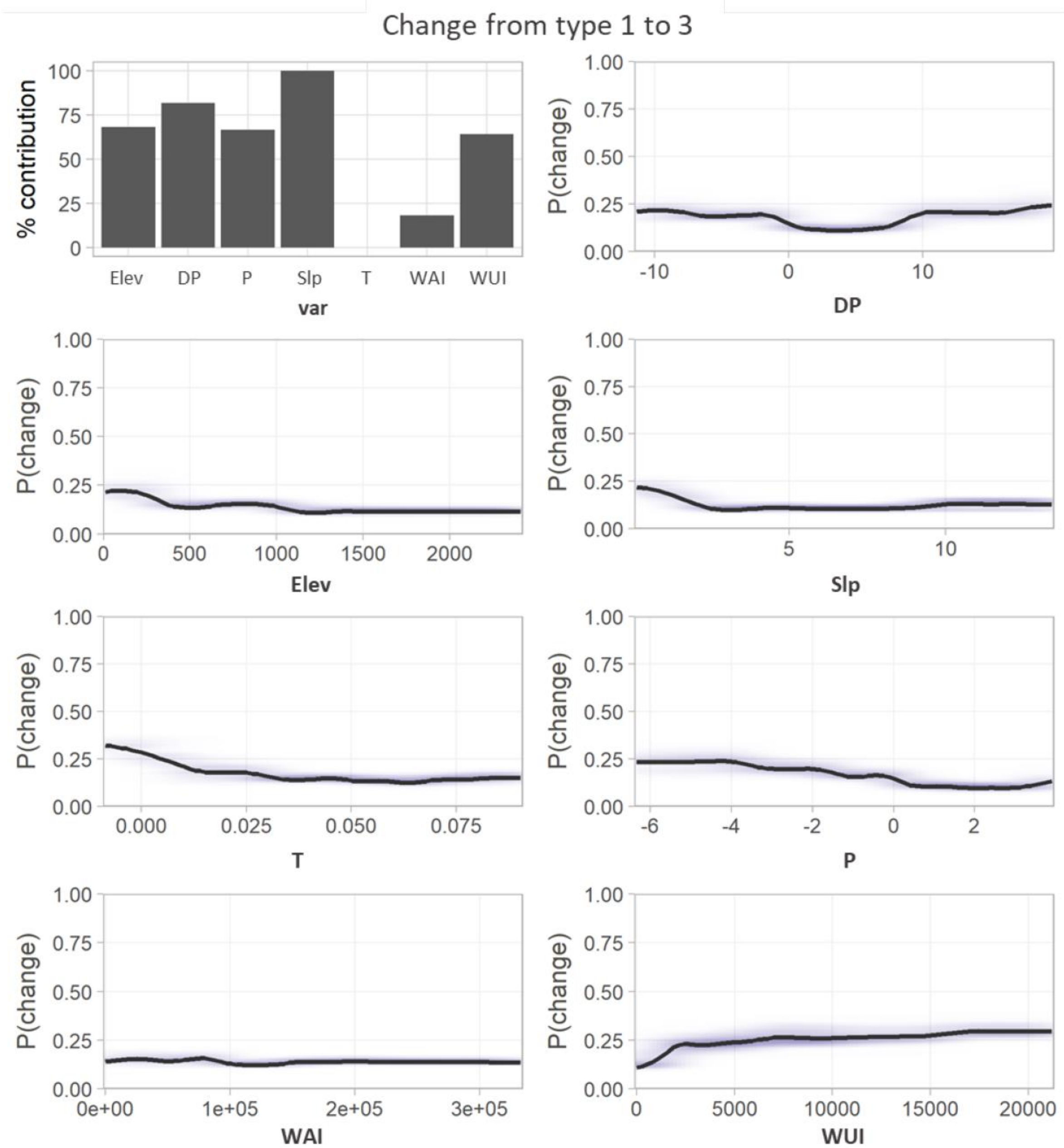

Fig. B2. Overall fire driver's contribution and the percentage of change for each explanatory variable in the fire regime transition **from type 1 to 3**. Elev: Elevation, DP: Demographic potential, P: Precipitation, Slp: Slope, T: Temperature, WAI: Wildland Agricultural Interface, WUI: Wildland Urban Interface.

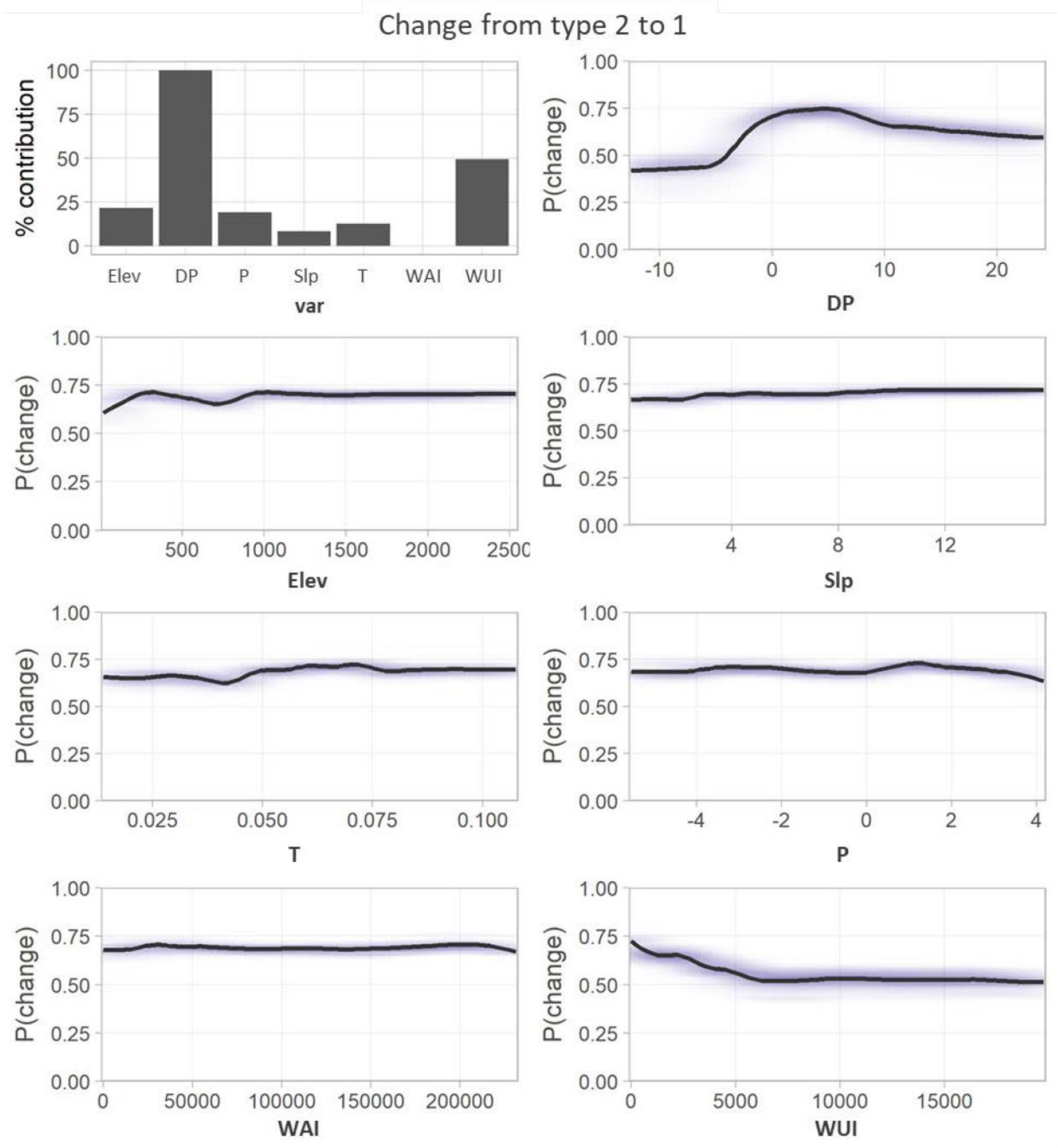

Fig. B3. Overall fire driver's contribution and the percentage of change for each explanatory variable in the fire regime transition **from type 2 to 1**. Elev: Elevation, DP: Demographic potential, P: Precipitation, Slp: Slope, T: Temperature, WAI: Wildland Agricultural Interface, WUI: Wildland Urban Interface.

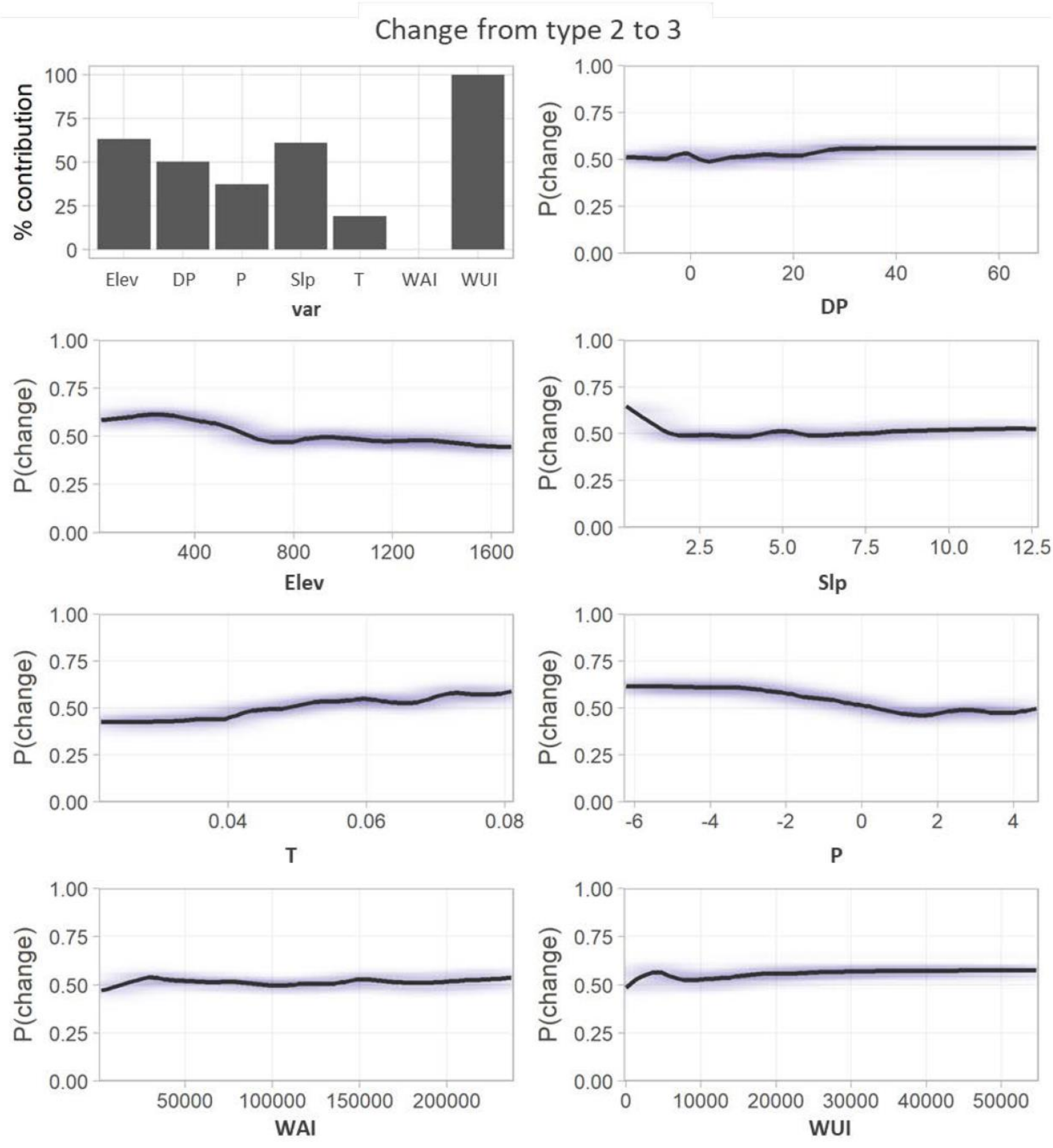

Fig. B4. Overall fire driver's contribution and the percentage of change for each explanatory variable in the fire regime transition **from type 2 to 3**. Elev: Elevation, DP: Demographic potential, P: Precipitation, Slp: Slope, T: Temperature, WAI: Wildland Agricultural Interface, WUI: Wildland Urban Interface.

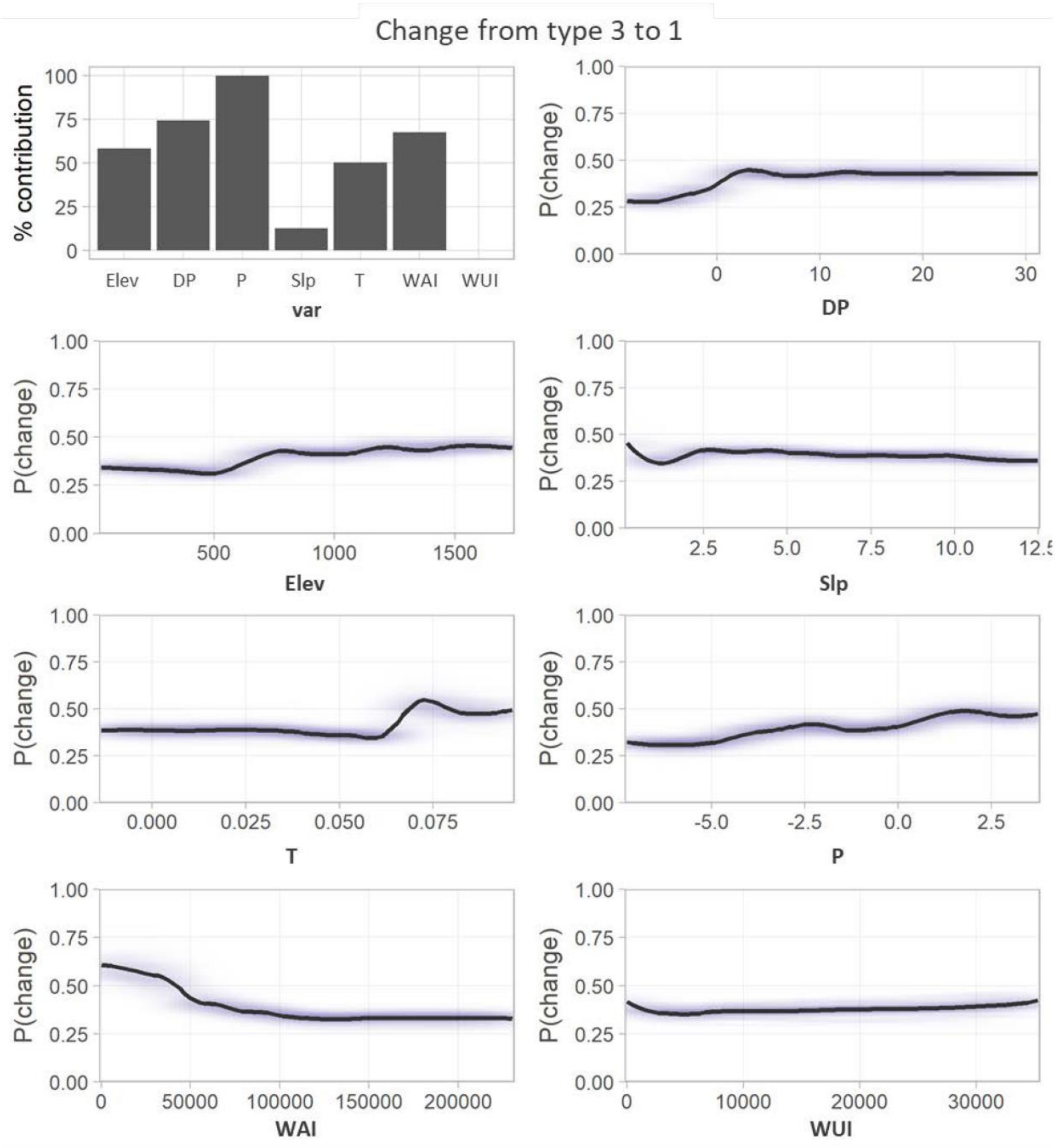

Fig. B5. Overall fire driver's contribution and the percentage of change for each explanatory variable in the fire regime transition **from type 3 to 1**. Elev: Elevation, DP: Demographic potential, P: Precipitation, Slp: Slope, T: Temperature, WAI: Wildland Agricultural Interface, WUI: Wildland Urban Interface.

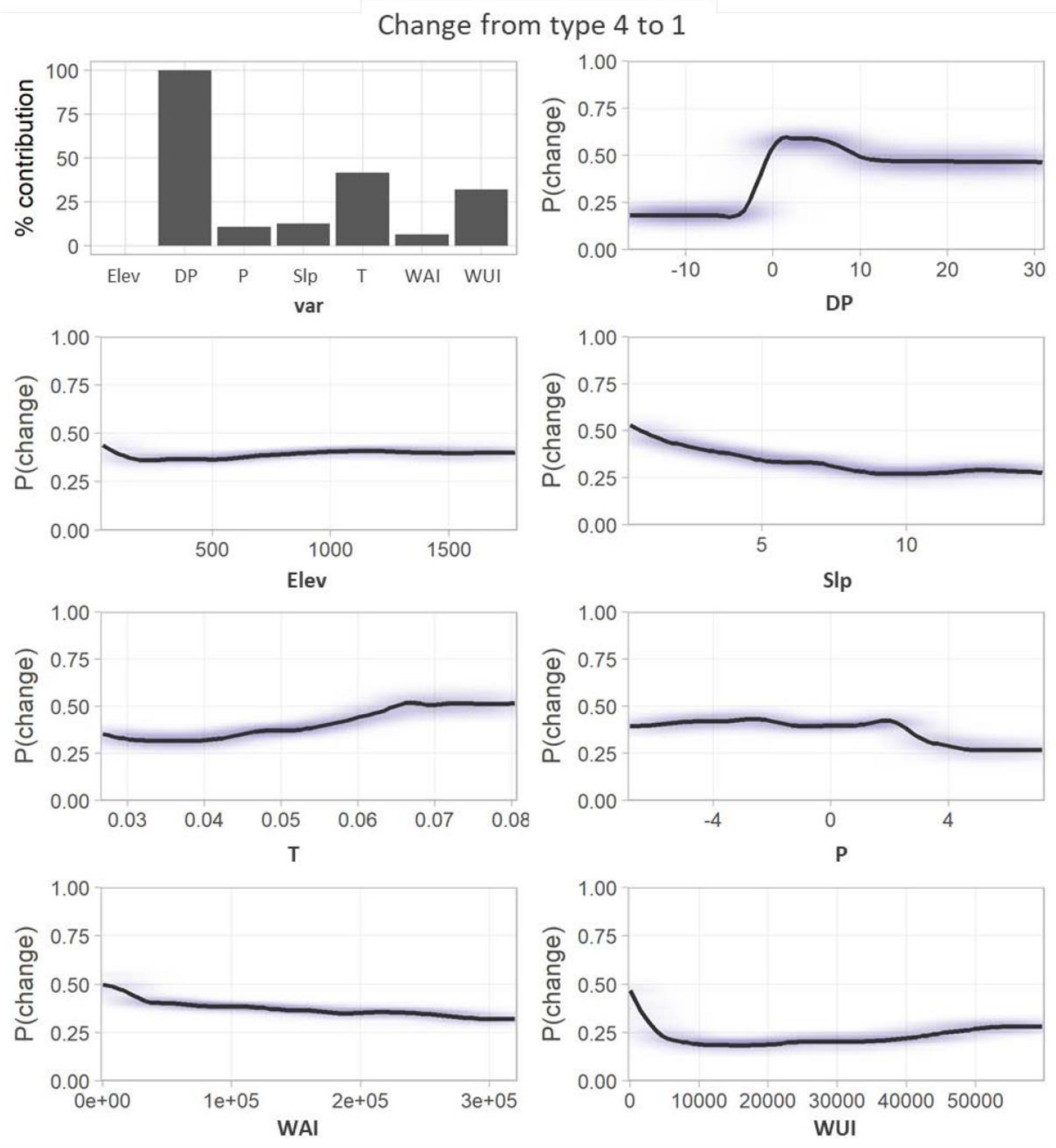

Fig. B6. Overall fire driver's contribution and the percentage of change for each explanatory variable in the fire regime transition **from type 4 to 1**. Elev: Elevation, DP: Demographic potential, P: Precipitation, Slp: Slope, T: Temperature, WAI: Wildland Agricultural Interface, WUI: Wildland Urban Interface.

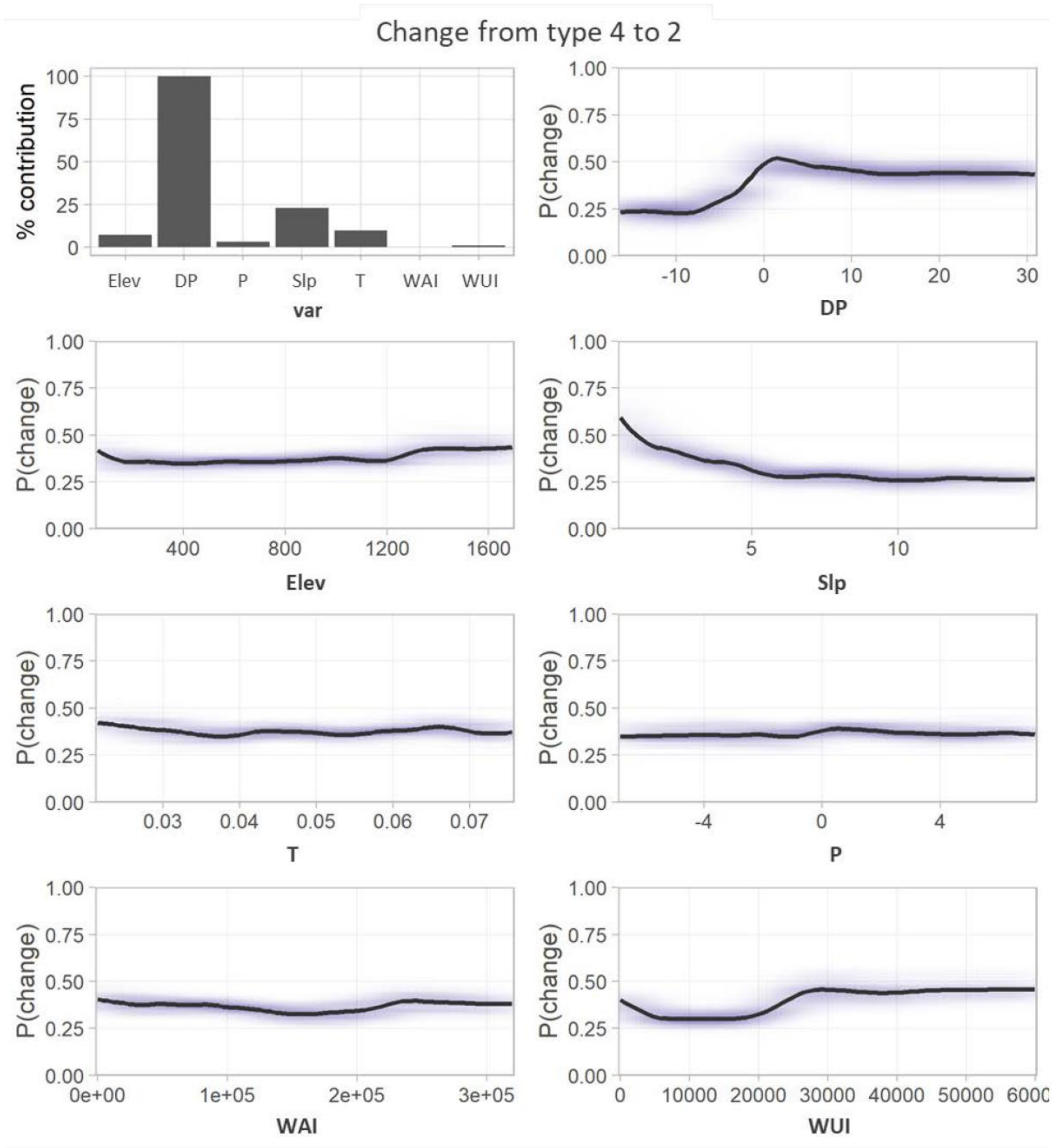

Fig. B7. Overall fire driver's contribution and the percentage of change for each explanatory variable in the fire regime transition **from type 4 to 2**. Elev: Elevation, DP: Demographic potential, P: Precipitation, Slp: Slope, T: Temperature, WAI: Wildland Agricultural Interface, WUI: Wildland Urban Interface.

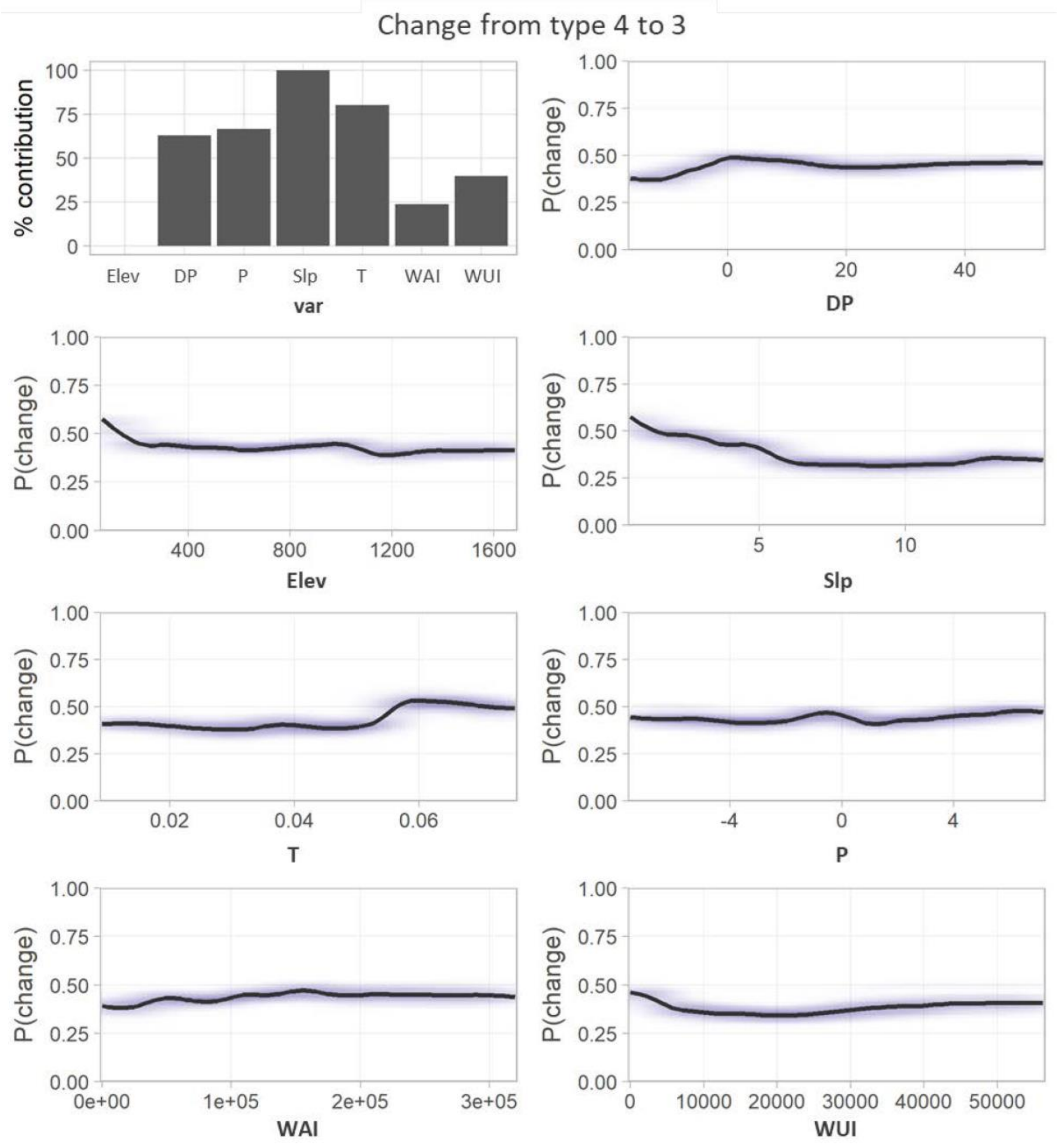

Fig. B8. Overall fire driver's contribution and the percentage of change for each explanatory variable in the fire regime transition **from type 4 to 3**. Elev: Elevation, DP: Demographic potential, P: Precipitation, Slp: Slope, T: Temperature, WAI: Wildland Agricultural Interface, WUI: Wildland Urban Interface.

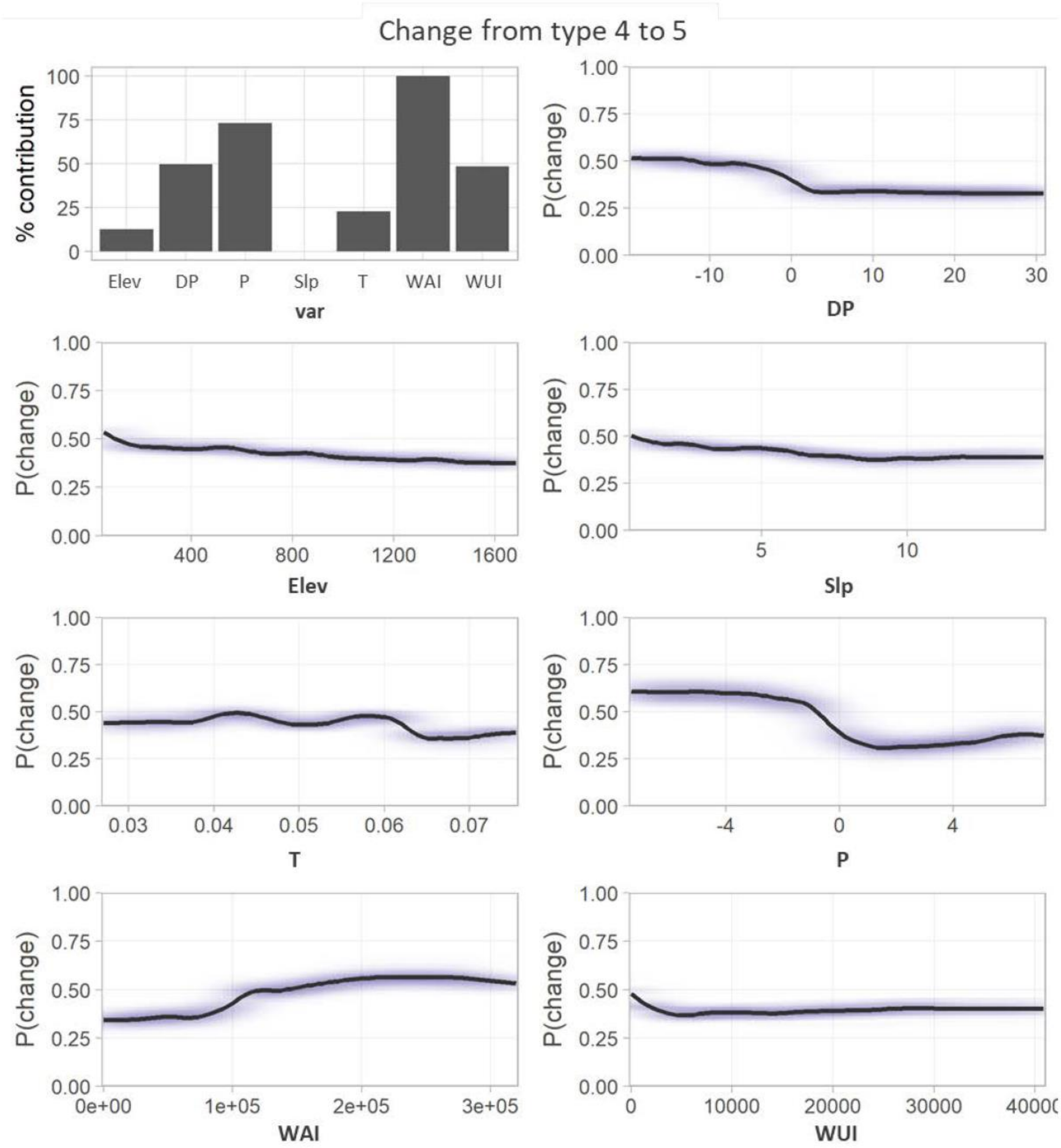

Fig. B9. Overall fire driver's contribution and the percentage of change for each explanatory variable in the fire regime transition **from type 4 to 5**. Elev: Elevation, DP: Demographic potential, P: Precipitation, Slp: Slope, T: Temperature, WAI: Wildland Agricultural Interface, WUI: Wildland Urban Interface.

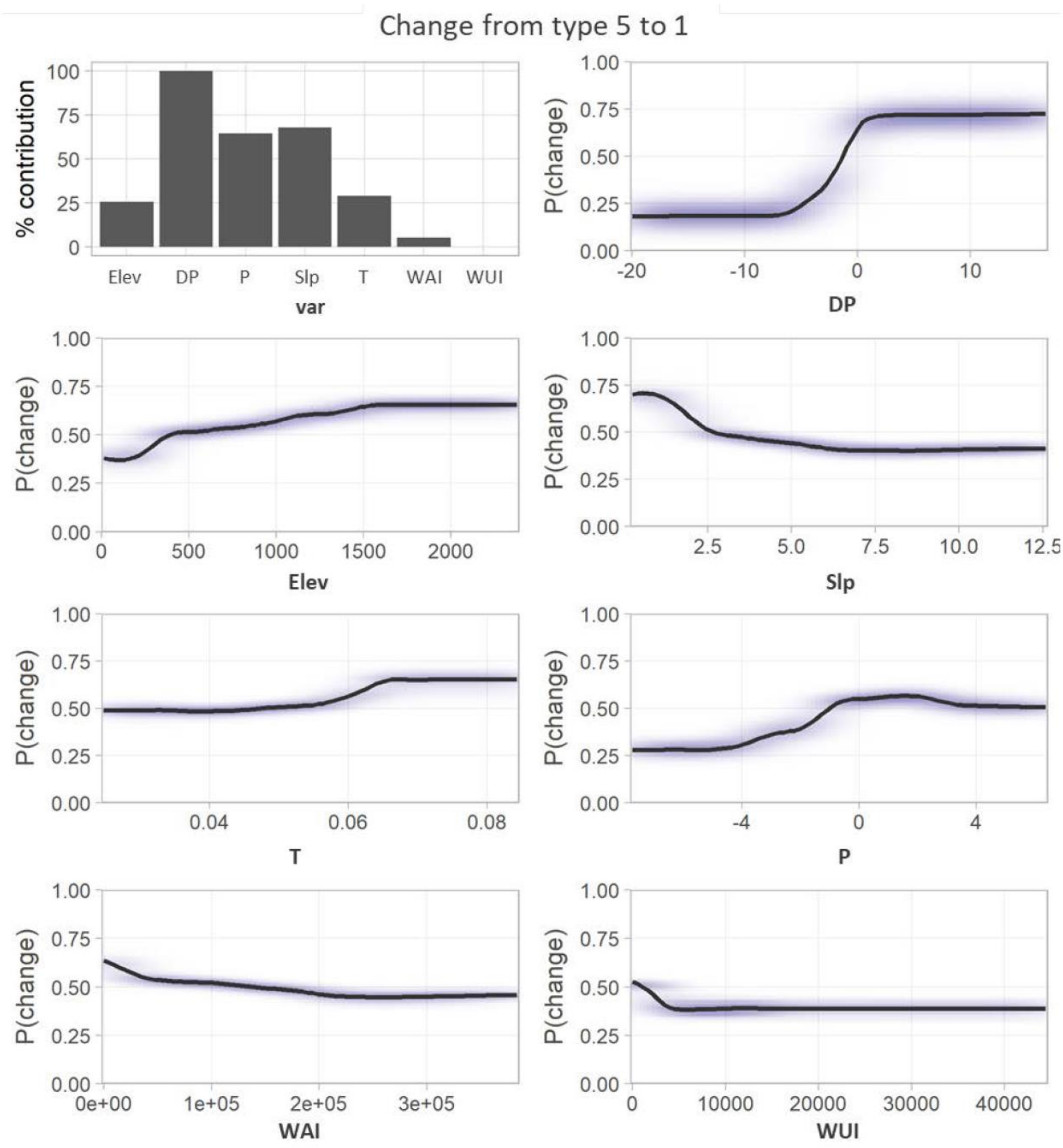

Fig. B10. Overall fire driver's contribution and the percentage of change for each explanatory variable in the fire regime transition **from type 5 to 1**. Elev: Elevation, DP: Demographic potential, P: Precipitation, Slp: Slope, T: Temperature, WAI: Wildland Agricultural Interface, WUI: Wildland Urban Interface.

D APPENDIX D: PRELIMINARY PYROREGIONS DELIMITATION

This appendix presents the work "Identifying pyroregions by means of Self Organizing Maps and hierarchical clustering algorithms in mainland Spain" forming part of the conference proceedings in *Advances in Forest Fire Research* 2018. It summarizes a preliminary attempt to define spatial-temporal definition pyroregions employing Self Organizing Maps (SOM), including the structural and trend component of fire regime features.

Advances in Forest Fire Research 2018 - D. X. Viegas (Ed.)
Chapter 3 – Fire Management
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Identifying pyroregions by means of Self Organizing Maps and hierarchical clustering algorithms in mainland Spain

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Abstract

Defining pyro-regions, i.e., of homogenous zones of fire activity, is an on-going task in Spain with few case studies in the literature. Their characterisation and understanding is a crucial step towards improving forest fire management and prevention. It is widely agreed that fire activity is non-stationary. Several works already report temporal dynamics in fire frequency and burned area. In this work we propose a spatial-temporal approach to define pyro-regions considering both structural and temporal fire behaviour using historical fire records from the EGIF database. A combination of Self Organizing Maps (SOM) and hierarchical clustering is applied to time series (1974-2015) of fire regime features: number/burned area of summer fires, number/burned area of large fires (>500 ha), number/burned area of natural fires, number/burned area of winter fires and number of small fires (<1 ha). The structural component of fire activity is computed as the average value whereas the temporal evolution is addressed by means of Sen's slope.

Prior to cluster analysis, fire features were submitted to Principal Component Analysis with Varimax rotation. Eigenvalues were then pre-classified using SOM. Subsequently, hierarchical clustering was applied to SOM outputs. We obtained a set of 4 structural clusters relating to increased number of fires; low fire incidence, slightly linked to winter season; large and natural fires; and moderate impact of human-related large fires mainly. The process was repeated using Sen's slope to build the dynamic component, ultimately characterised by: highly dynamic winter with increased in summer frequency; increased summer burned area and natural fires; and small fires; and no trend.

Keywords: forest fires, pyro-regions, Sen's Slope, SOM, hierarchical clustering, Spain

1. Introduction

Forest fires are a highly complex phenomenon affecting most ecosystems worldwide. Fire is known as a natural process responsible for the evolution of wild communities, but nowadays it has been altered, with potential undesired effects on vegetation structure, composition and ecosystemic functions. Fire activity is controlled by multiple factors such as climate, fuel, physiography and human activity. Humans influence fire incidence acting as both initiators and suppressors, increasing the complexity of the phenomena. Thus, understanding fire regime's components and behaviour (both temporal and spatial) may improve our current knowledge. Mapping fire regimes may contribute enhancing fire planning or risk assessment; as well as diminishing undesired ecological impacts (Morgan *et al.* 2001). In this sense, one of the most promising lines of study lies in the definition and characterization fire regime itself. Fire regime is usually described using several quantifiable parameters such as affected area, fire frequency, cause, seasonality, fire size, etc. (Boulanger *et al.* 2014). Currently, there still is an open debate on the definition of the concept itself, with slight variations depending on the scale of analysis, the length of the study period or the available information.

Several attempts to define fire regimes from different approaches are already found in the literature. Without being exhaustive we find some analyses using remote sensing data (Chuvieco *et al.* 2008) or climate information (Boulanger *et al.* 2013, 2014; DaCamara *et al.* 2014). Others employ fire weather danger indexes coupled to fuel and environmental conditions (Perera and Cui 2010). Despite of the success in the characterisation of fire regime, most works still rely on existent zoning schemes to spatialize their boundaries and extent: administrative units (Pereira *et al.* 2015), ecoregions (Malamud *et al.* 2005; Kasischke and Turetsky 2006; Perera and Cui 2010; Mori and Johnson 2013) or a combination of both (Wotton *et al.* 2010).

In the case of Spain, examples of fire regime zoning are really scarce, with Moreno and Chuvieco (2013) as the most representative effort. We find other examples in Vázquez de La Cueva *et al.* (2006) and more recently in Montiel Molina and Galiana-Martín (2016). These approaches are mostly based on cluster analysis, the most used and well-known zoning approach. They are a flexible multivariate technique with different available implementations, widely used to analyse ignition points distribution (Wang and Anderson 2010; Serra *et al.* 2013; Pereira *et al.* 2015; Parente *et al.* 2016) or occurrence large fire linked to synoptic climatology (Rasilla *et al.* 2010). Nevertheless, all of them provide a static picture of fire regime, i.e., disregarding the evolution of fire features over time and space. For this reason, a temporal perspective is extremely necessary.

In this work we propose and exemplify a method to outline homogenous fire regime zones (the so-called pyroregions) in mainland Spain. We combine average information of fire features with their temporal evolution (trend detection) during the study period (1974-2015). The method is based on PCA and Self Organizing Maps coupled to hierarchical clustering. Such combination of methods is applied to the averaged values of fire features and their respective trends, separately. By doing so we are able to discriminate static and dynamic pyroregions.

2. Materials and methods

2.1. Study area

The study area encompasses the whole mainland Spain covering a surface of around 498,000 km^2. Climate distribution in the region allows to differentiate two regions: Mediterranean and Oceanic. The first one is characterized by high annual thermal amplitude with hot-summer in the inner region and milder conditions towards the coast. Precipitation is irregularly distributed both in terms of time and space, with maximums peaking in autumn and spring. In addition, the driest areas are located in the southeast region and the Ebro Valley (inner Mediterranean region). On the other hand, Oceanic climate is notable by milder temperature values during summer-winter with high precipitation values regularly distributed throughout the year (average values over 1,000 mm) with maximum during winter. From the biogeographical point of view, the Oceanic area is covered by diverse types of vegetation from deciduous to evergreen oak woodlands (*Quercus robur, Fraximus excelsior* or *Fagus sylvatica*) and large areas of scrubland and grassland, as well as areas with afforestation of fast-growing species such as *Pinus radiata* and *Eucaliptus globulus*. The Mediterranean vegetation coexists with complex mosaics of agricultural systems and plant communities, such as sclerophyllous and evergreen vegetation. Oak (*Quercus ilex*) and pine (mainly *Pinus halepensis,* the most widespread of the species introduced by afforestation) forest, and thermophilous scrubland, dominate the region. In addition, altitudinal belts exist within the highest ridges such as the Pyrenees along the French border or Sierra Nevada on the southern Mediterranean coast, being home to a large variety of tree species which are common in central Europe (deciduous species, beech, oak, and some mountain pines: *Pinus uncinata, Pinus sylvestris*).

2.2. Fire data

Fire records in the period 1974-201 5 were collected from the General Wildfire Statistics (EGIF). Selected fire records were on a 10x10 km UTM reference grid. Then, fire frequency, total burned area (ha), ignition date and source were extracted from the database. Is it important to note, that only those grids with at least a 25% of forest cover were retained for analysis. Therefore, 3,308 out of 5200 grids were finally considered in the analyses.

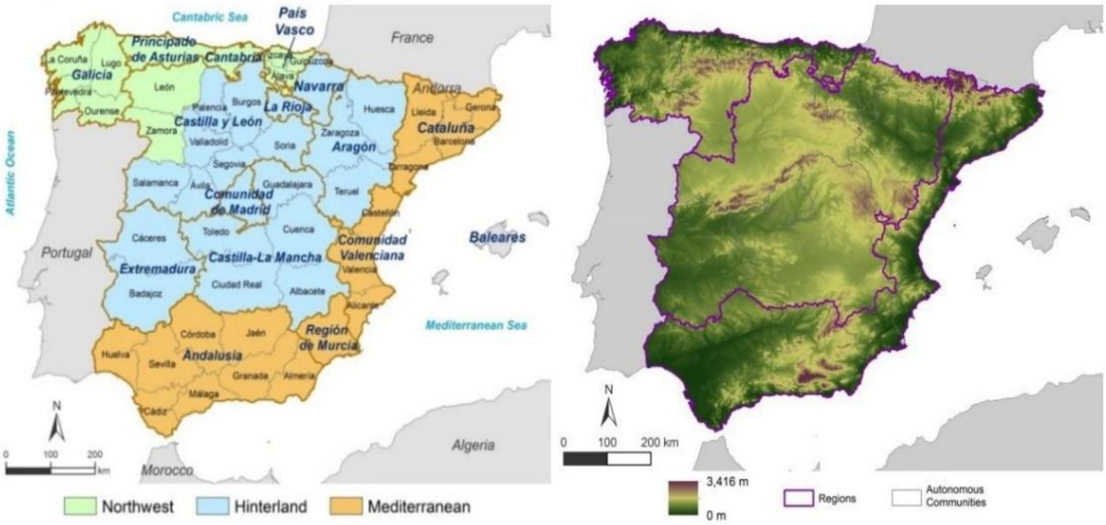

Figure 1 - Spatial distribution of the three regions (Northwest, Hinterland and Mediterranean) also NUTS3 and NUTS2 units in mainland Spain (left) and digital elevation model (right)

Two fire seasons were defined with the aim of differentiating the intra-annual peaks of fire activity (August and March). So, annual fire data were split into spring – summer season (S), from April to September; and autumn-winter season (W) from October to March. From all available fire information, we computed 9 fire features: number of fires and burned area during summer (NS-BAS), summer frequency and burnt area of large fires –above 500 ha– (N500, B500), summer frequency and burnt area of natural fires (NL-BL), number of fires and burnt area during winter (NW-BAW) and total number of small fires (N <1 ha).

2.3. Temporal evolution of fire features

In order to account for the temporal dimension of fire activity during the analyzed time span we estimated the magnitude of the temporal change using Sen's slope (Sen 1968) test. This allows to outline fire zones according to the temporal behavior of fire features rather than address the average 'structural' pattern alone.

2.4. Environmental and human factors

To characterize the final pyroregions we used data related with environmental and human factors. Temperature and precipitation data in the period 1974-2010 were extracted from MOTEDAS (González-Hidalgo *et al.* 2015) and MOPREDAS (González-Hidalgo *et al.* 2011) datasets (Figure 3). Additionally, forest communities were derived from the Forest Map of Spain. Finally, the Human Pressure Index (Figure 2) was calculated according to Jiménez-Ruano *et al.* (2017).

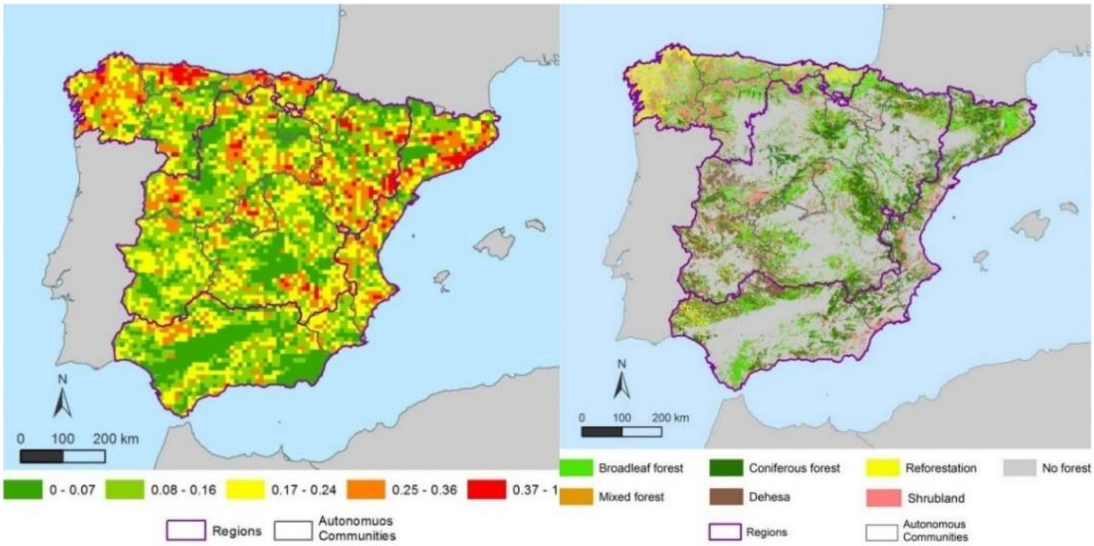

Figure 2 - Spatial distribution of the Human Pressure Index (left) and main forest formations from National Forest Map (right).

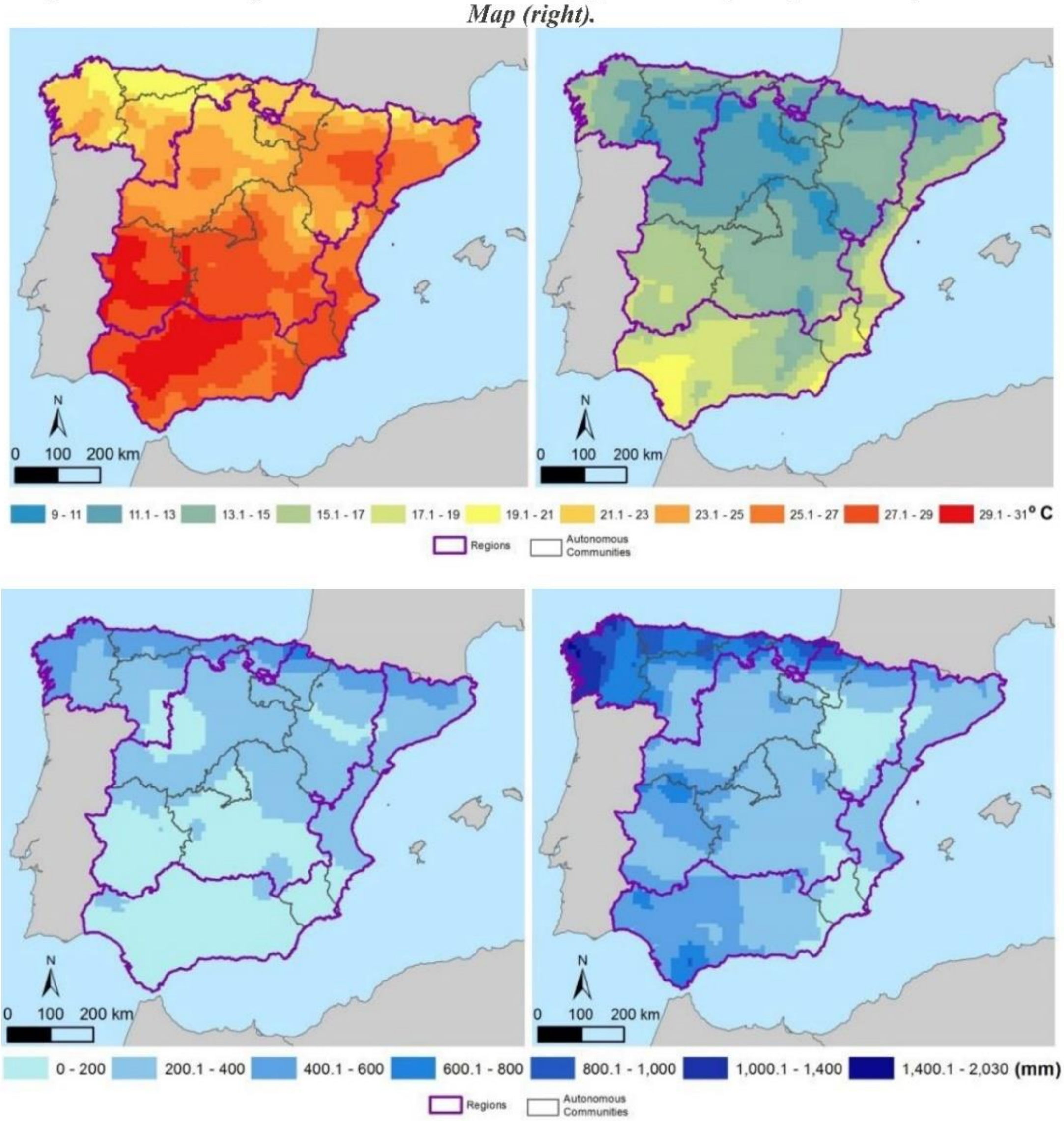

Figure 3 - Climate factors. Top-left, average summer temperature; top-right, average winter temperature; bottom-left, summer mean annual precipitation; bottom-left, winter mean annual precipitation

2.5. Principal Component Analysis and Varimax rotation

Prior to submit fire data to cluster analysis, a PCA with varimax rotation was applied to reduce the amount of information. All fire features (both structural and dynamic) were scaled before applying PCA. Principal Components (PC) were selected according to the Kaiser Criterion, i.e., only those PC with standard deviation over 1 were retained.

2.6. Clustering overview

The objective of clustering analysis is grouping objects into categories such that objects within one cluster share more in common with one another than they do with the objects of other clusters (Gore 2000). Many clustering algorithms do exist. The most basic variants resort to data partition and minimizing the distance between points of a same group from another assigned as center. Among all the clustering methods, we selected hierarchical clustering coupled to Self-Organizing Maps to delineate our pyroregions.

The purpose of hierarchical clustering is determinate the best clustering scheme from different results obtained. It is proceeded with the application of various combinations of number of clusters, distance measures and clustering methods. This algorithm routinely produce a series of solutions ranging from *n* clusters to a solutions with only one cluster present (Charrad *et al.* 2014). It requires a dissimilarity measure (or distance) and an agglomeration criterion. Many distances area available (Manhattan, Euclidean, etc.) as well as several agglomeration methods (Ward, single, centroid, etc.). In our case, we employed all methods available in the *NbClust* function from RStudio, the Canberra distance and the Ward D2 method (Murtagh and Legendre 2014), which minimizes the total within-cluster variance and the dissimilarities are squared before cluster updating.

SOM is a neural-network algorithm that implements an orderly mapping whose main strength lies in converting complex and non-linear relationships between high-dimensional data (Kohonen 1998). In other words, it compresses information while keeping topological and metric relationships of the input data. The algorithm consists of a two-dimensional model of regular grid of nodes, where some data are associated with each node. In each iteration, the SOM algorithm computes all the models to best describe the domain of the observations. The idea is to group the similar models that are closer to each other in the grid than the more dissimilar ones.

As aforementioned the cluster approach was applied both to 'structural' and 'dynamic' components, thus 2 sets of cluster were obtained. In a final step we overlay all clusters (structural and dynamic) to into the final pyroregions.

3. Results

Figures 4 and 6 show the spatial distribution of the structural (4) and dynamic (3) clusters, and their description, respectively. First structural cluster characterises by high fire activity but no large fires; it extends across the Northwest region. In turn, cluster 2 comprises areas of moderate winter activity, in the remaining territory. Cluster 3 brings together summer large fires (>500 ha) caused by lightning. This cluster covers mostly mountain ranges. Finally, cluster 4 brings together medium-size human-caused fires.

Dynamic clusters depict a different behaviour. Tendencies were grouped into clusters 1 and 3. In the first case, winter trends and the increase in summer small fires are grouped in cluster 1. Geographically, these trends are located in the north-western end, some locations of the inland mountain ranges and few spots of the Mediterranean basin. Remaining trends depict an increase in overall area burned during summer and decreased incidence of natural fires (Table 1), occupying an area that mainly extends over the northern and northwest hinterlands.

When combining both cluster approaches into a single product we obtain a final set of 8 pyroregions (Figures 5 and 6). Generally speaking, three main groups of pyroregions can be distinguished: (1) those experiencing increase in the fire activity, especially small fires; (2) regions with no noticeable trend; and (3) those characterised by increased summer burnt area and lightning-triggered wildfires.

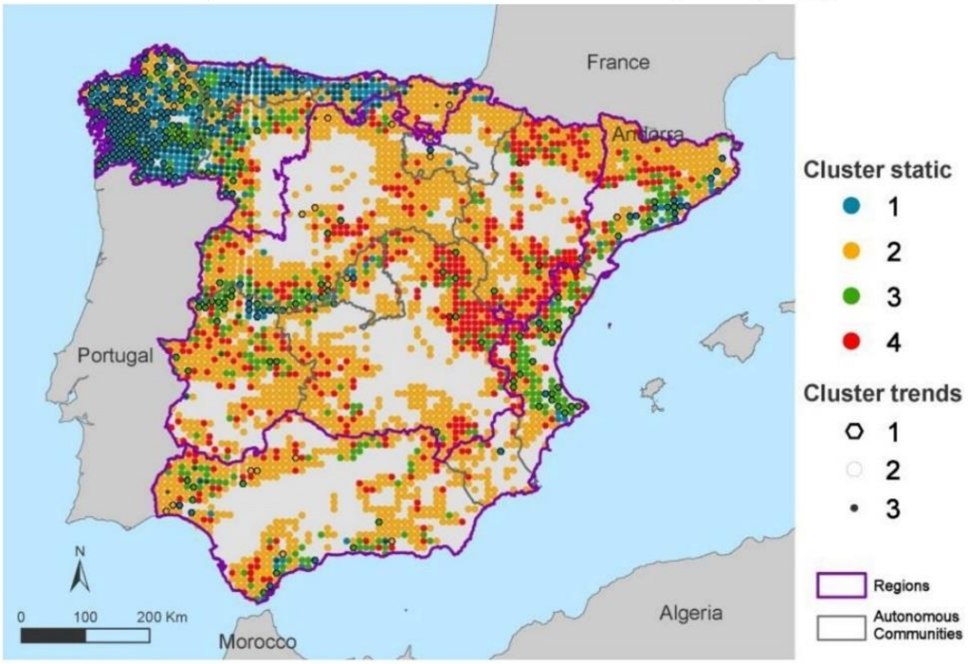

Figure 4 - Spatial distribution of the clusters structural (colour codes) and dynamic (shape codes).

Table 1 - PCA-Varimax eigenvectors of the first two components of static (fire features averages) and the first three components for trends in fire features

	Fire features	NS	BAS	N500	B500	NL	BL	NW	BAW	N <1ha
Static	PC1	**0.526**	0.148				-0.152	**0.526**	0.328	**0.529**
	PC2		**-0.508**	-0.436	**-0.581**	-0.212	-0.408			
Trends	PC1	**0.534**	-0.271					**0.512**	0.262	**0.557**
	PC2					**-0.702**	**-0.705**			
	PC3		**0.674**					0.230	**0.672**	-0.203

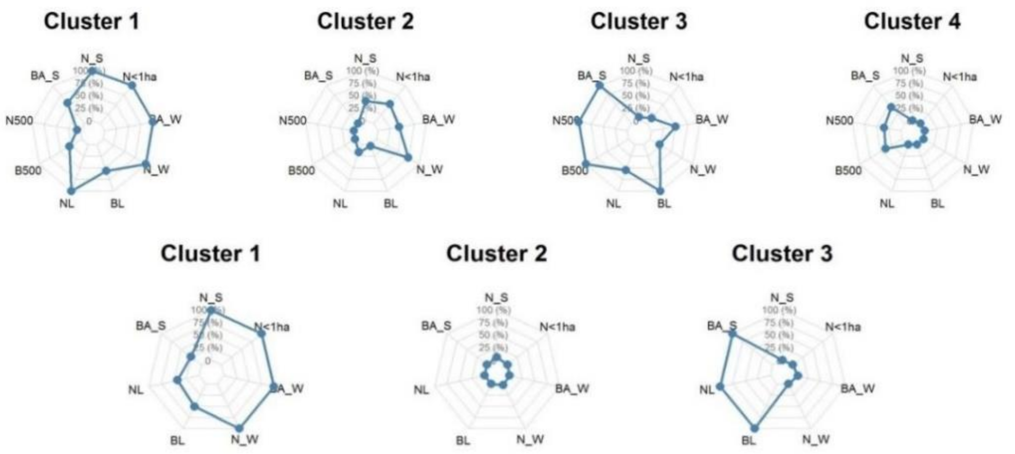

Figure 5 - Description of the contribution percentage for each fire feature in each cluster static (four on the top) and in each cluster of trends (three on the bottom)

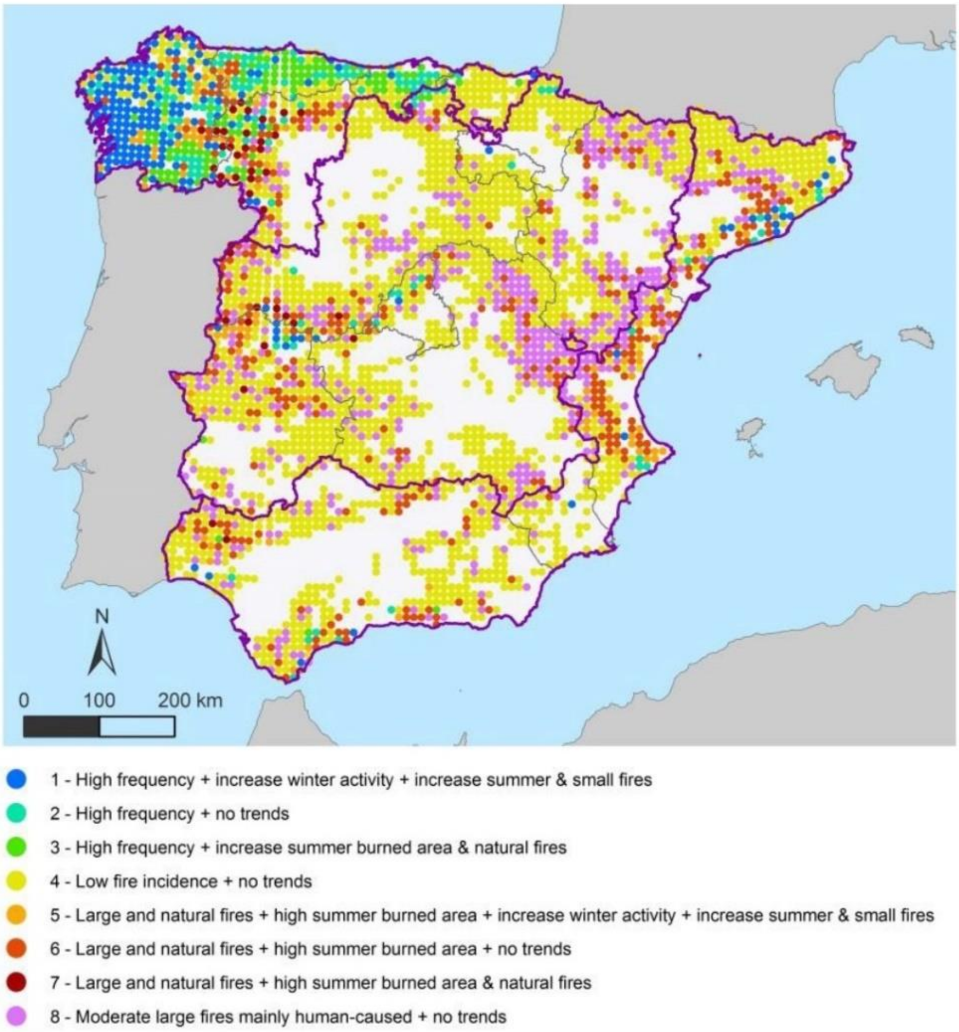

Figure 6 - Spatial distribution of the final pyroregions

The most relevant pyroregion in terms of spatial extent is 4 (55.1%), characterized by a low fire incidence without trends. Secondly, pyroregion 8, covering 16.4% of the territory, is represented by medium-sized fires mainly anthropogenic. With a 10.2% of the study area, pyroregion 6 combines large and natural fires with an increase in summer burned area. Pyroregion 1 (5.4% area) is mainly located in the Northwest region. It shows a high fire frequency linked to winter dynamics, as well as an increase in summer and small fires. Remaining pyroregions account for just over 1% and less than 4% individually. In summary, they would reach roughly 11.6% of the territory. These are characterized by a high frequency with no trends (2), or with an increase in summer burnt area and natural fires (3). In addition, large fires with an increase in summer-winter activity and small fires (5) and large fires associated with an increase in summer burnt area and natural fires (7).

3.1. Characterization of pyroregions based on environmental and human variables

The inclusion of climate-and-human variables enables deeper insights into the characterisation of the pyroregion (Figure 7):

Pyroregion 1: small winter fires and increased summer fire activity. It covers conifer and reforested communities with large rainfall and moderate warm winters and low human pressure.

Pyroregion 2: low fire activity in areas with moderate rainfall, temperate winters and summers.

Pyroregion 3: increasing winter fire incidence in shrubland communities linked to increased human pressure, large precipitation and moderate temperatures.

Pyroregion 4: low fire activity in isolated warm regions with conifer and mixed forest.

Pyroregion 5: low fire activity increasing during summer. It covers warm and dry regions with a variety of forest communities. Low human pressure.

Pyroregion 6: large natural fires with moderate-low human pressure, high temperature and low rainfall; affecting the whole spectrum of forest communities.

Pyroregion 7: very low fire activity in shrubland communities.

Pyroregion 8: natural fires in warm and dry locations affecting tree communities.

4. Discussion

The proposed methodology enabled identifying 8 pyroregions providing a more complete picture than previous attempts. We took a step further, not only by bringing in the dynamic component of fire incidence but digging into more sophisticated zoning techniques. Our contribution further deepens into fire features while complementing them with their main trends such as the rise in summer and winter activity or the increase in small fires.

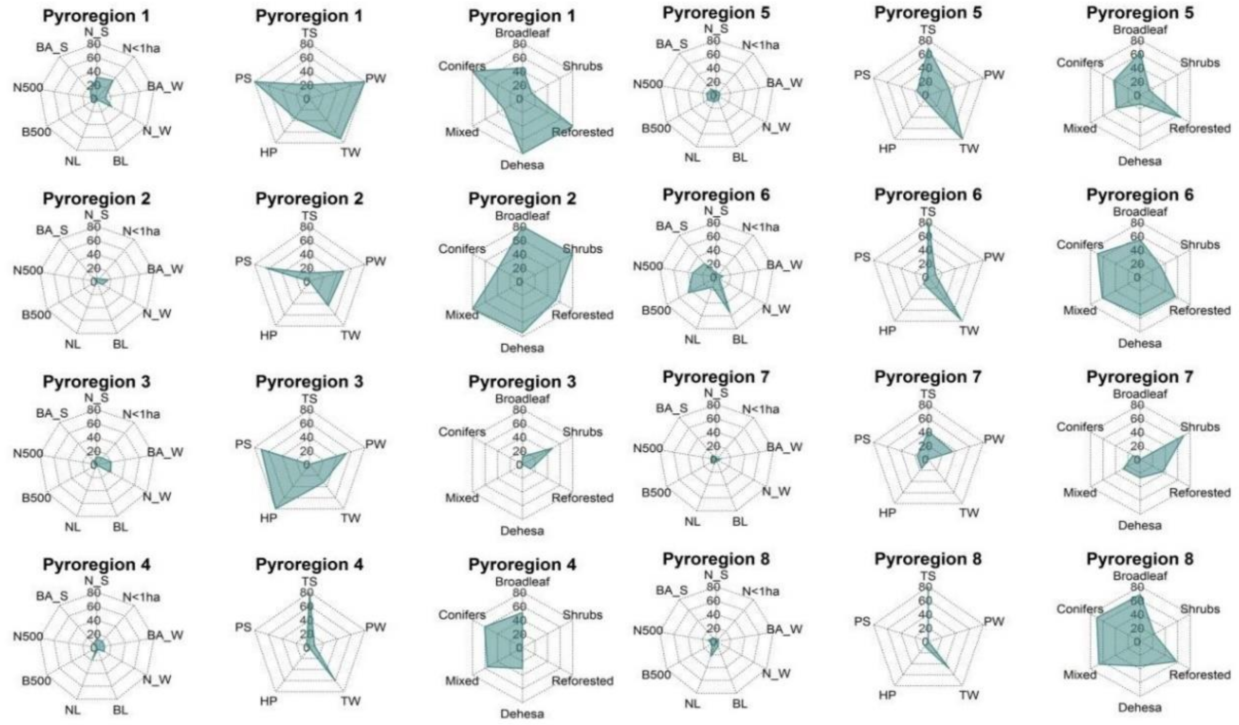

Figure 7 - Pyroregion description. Left column, fire features; center, environmental and human drivers; right, forest communities.

When combining the resulting pyroregions with climatic and human factors, we deliver deeper insights into what factors may be driving fire regimes. Our findings suggest coincidence between temporal clusters of increased fire activity (except for natural fires) dominated by pine woodland and reforestation communities (Vázquez *et al.* 2015). In many areas of Spain, plantations for timber harvesting and pine tree forests were promoted over the last decades (Pausas *et al.* 2004). This factor is known to increase flammability in the event of favourable weather conditions (Shakesby 2011).

Regarding climatic factors, fire-prone conditions along the Mediterranean coast seem to promote larger human-cause fires, especially during summer. However, the correspondence of climate with trend clusters is not clear. In this sense, the human impact (represented here as the combination of the length of wildland-urban and wildland-agricultural, WUI-WAI interfaces and demographic potential) seems to be more closely related with fire activity (Rodrigues and de la Riva 2014).

5. Conclusions

In this work we propose a pyrogeographical characterization of fire behaviour using averaged of fire features and their main temporal trends in mainland Spain. We submitted fire data in the period 1974-2015 to PCA and cluster analysis.

Our findings suggest 8 different pyroregions in mainland Spain, depicting by three structural fire regimes (high fire frequency, large-natural fires and medium size human-cause wildfires) and two main trends (overall increase in fire activity) and decrease in the incidence of natural fires. The implications of the delimited pyroregions play a crucial role in better understanding fire regimes in a broad context, not only in terms of their structural patterns but also of its main trends. Moreover, assessing the environmental and human conditions in the proposed pyroregions improved our understanding of the underlying drivers of fire regimes.

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E

APPENDIX E: CONFERENCES CONTRIBUTIONS

This appendix brings together several abstracts from different conference contributions, mainly from the European Geosciences Union General Assembly (EGU) held in 2017 and 2018. Most of the abstracts refers to poster presentations and one to an oral dissertation.

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Vol. 19, EGU2017-15084, 2017
EGU General Assembly 2017

An analysis of wildfire frequency and burned area relationships with human pressure and climate gradients in the context of fire regime

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Understanding fire regime is a crucial step towards achieving a better knowledge of the wildfire phenomenon. This study proposes a method for the analysis of fire regime based on multidimensional scatterplots (MDS). MDS are a visual approach that allows direct comparison among several variables and fire regime features so that we are able to unravel spatial patterns and relationships within the region of analysis. Our analysis is conducted in Spain, one of the most fire-affected areas within the Mediterranean region. Specifically, the Spanish territory has been split into three regions – Northwest, Hinterland and Mediterranean – considered as representative fire regime zones according to MAGRAMA (Spanish Ministry of Agriculture, Environment and Food). The main goal is to identify key relationships between fire frequency and burnt area, two of the most common fire regime features, with socioeconomic activity and climate. In this way we will be able to better characterize fire activity within each fire region.

Fire data along the period 1974-2010 was retrieved from the General Statistics Forest Fires database (EGIF). Specifically, fire frequency and burnt area size was examined for each region and fire season (summer and winter). Socioeconomic activity was defined in terms of human pressure on wildlands, i.e. the presence and intensity of anthropogenic activity near wildland or forest areas. Human pressure was built from GIS spatial information about land use (wildland-agriculture and wildland-urban interface) and demographic potential. Climate variables (average maximum temperature and annual precipitation) were extracted from MOTEDAS (Monthly Temperature Dataset of Spain) and MOPREDAS (Monthly Precipitation Dataset of Spain) datasets and later reclassified into ten categories. All these data were resampled to fit the 10x10 Km grid used as spatial reference for fire data.

Climate and socioeconomic variables were then explored by means of MDS to find the extent to which fire frequency and burnt areas are controlled by either environmental, human, or both factors. Results reveal a noticeable link between fire frequency and human activity, especially in the Northwest area during winter. On the other hand, in the Hinterland and Mediterranean regions, human and climate factors ‘work’ together in terms of their relationship with fire activity, being the concurrence of high human pressure and favourable climate conditions the main driver. In turn, burned area shows a similar behaviour except in the Hinterland region, were fire-affected area depends mostly on climate factors. Overall, we can conclude that the visual analysis of multidimensional scatterplots has proved to be a powerful tool that facilitates characterization and investigation of fire regimes.

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Assessing the influence of small fires on trends in fire regime features at mainland Spain

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Small fires, i.e. fires smaller than 1 Ha, represent a huge proportion of total wildfire occurrence in the Mediterranean region. In the case of Spain, around 53% of fires in the period 1988-2013 fall into this category according to the Spanish EGIF statistics. However, the proportion of small fires is not stationary over time. Small fires are usually excluded from most analysis, given the chance of introducing or falling into temporal bias, being almost mandatory in those assessments using data before the 90s. Inconsistences and inhomogeneity problems related to the diversity of criteria and/or registration procedures among Autonomous Regions are found before that date, although it is widely agreed that small fires are consistently registered starting from 1988. Nevertheless, in terms of fire regimen characterization it is important to know to what extent small fires contribute to the overall fire behaviour.

The aim of this study is to analyse spatial-temporal trends of several fire features such as total number of fires and burned area, number and burned area of natural and human fires, and the proportion of natural/human cause in the period 1988-2013 at province level (NUTS3). The analysis is conducted at the mainland Spain at annual and seasonal time scales. We are mainly interested in exploring differences in spatial-temporal trends including or excluding small fires and dealing with them separately as well. This allows determining the extent to which small fires may affect fire regime characterization. We employed a Mann-Kendall test for trend detection and Sen's slope to evaluate the magnitude of the change. Both tests were applied for each fire feature aggregated at NUTS3 level for both autumn-winter and spring-summer seasons.

Our results show significant changes in the evolution of annual wildfire frequency; especially strong when small fires are accounted for. A similar outcome was observed in natural and human number fires during the spring-summer season. The increase in number of fires seems to be reversed during autumn-winter. At seasonal scale, the inclusion of small fires allows to detect significant trends in all of fire frequency features, except natural fires. In turn, neither burned area features do not significantly affect the trends through incorporating small fires. Therefore, the inclusion/exclusion of small fires do influence observed trends mostly in terms of fire frequency.

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Assessing the influence of fire weather danger indexes on fire frequency and burned area in mainland Spain

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Fire danger rating indexes based on weather data are a well-established way to identify favorable ignition-spread conditions. In this study, we investigate the association between FWI (Canadian Fire Weather Index), BI (US Burning Index) and FFDI (Australian Forest Fire Danger Index) with fire occurrence (N) and burnt area size (BA) at regional level in Spain. Fire indexes were retrieved from the European Centre for Medium-Range Weather Forecasts (ECMWF) Interim Reanalysis, later aggregated into a Composite Fire Danger Index (CFDI) which is calculated as the average normalized value of FWI, BI and FFDI. Fire frequency and burnt area statistics were calculated from the Spain's General Statistics on Wildfires database.

Monthly time series (from 1979 to 2013) of CFDI, N and BA were constructed and later decomposed into seasonal and trend components, representative of the intra-annual cycles and the temporal evolution of fire activity, respectively. The resulting series are then compared by means of cross-correlation functions (CCF). CCF allows identifying lags in the association between two variables. Here, we applied CCF to the decomposed time series of CFDI, N and BA exploring several lags (-3, -2, -1 and 0 months). Additionally, we applied the Mann-Kendall test to the trend component so that we can detect significant trends. The proposed method was applied using two spatial scales. In a first attempt we split Spain into three regions – Northwest (NW), Hinterland (HL) and Mediterranean (MED) – providing a broader picture. In a second stage we used a more spatial-explicit approach, applying CCF on a pixel-basis (0.75x0.75º), allowing mapping correlation values.

Regional results reveal a strong positive association between N, BA and CFDI for 0 and -1 lag comparisons. Overall, cross-correlations are greater in the HL (Nl=0=0.74, Nl=-1=0.59; BAl=0=0.60, Bal=-1=0.45) and MED (Nl=0=0.64, Nl=-1=0.48; BAl=0=0.43, Bal=-1=0.23) regions, and higher in the case of number of fires. The NW region shows moderate correlations (Nl=0=0.43, Nl=-1=0.29; BAl=0=0.50, Bal=-1=0.36) possibly due to its differential intra-annual behavior, with a secondary occurrence peak during winter way larger than the other regions. This secondary maximum is linked with human activities rather than weather conditions, which may explain the low correlation values. In the case of the trend component an increase in CFDI is detected. In turn, according to Mann-Kendall, N shows significant and positive trends in NW and HL, while MED experienced decreased fire occurrence. BA showed non-significant trends in all the study area excluding MED, with a negative trend. However, correlation values depict a different scenario than that from the seasonal component. No association is detected in NW (N,BAl=n≈0). The combination of negative trend in N and BA and overall positive trend in CFDI produces negative correlations values (N,BAl=n<0.3). The only region with positive association is observed in N in HL (Nl=n>0.4). We can conclude that weather conditions control intra-annual variation of fire activity but has limited influence on long-term trends. The spatial disaggregation of the CCF yields positive association of CFDI and N both for season and trend components in part of Spain.

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The role of drought length and magnitude in the temporal evolution of fire occurrence and burned area size in mainland Spain

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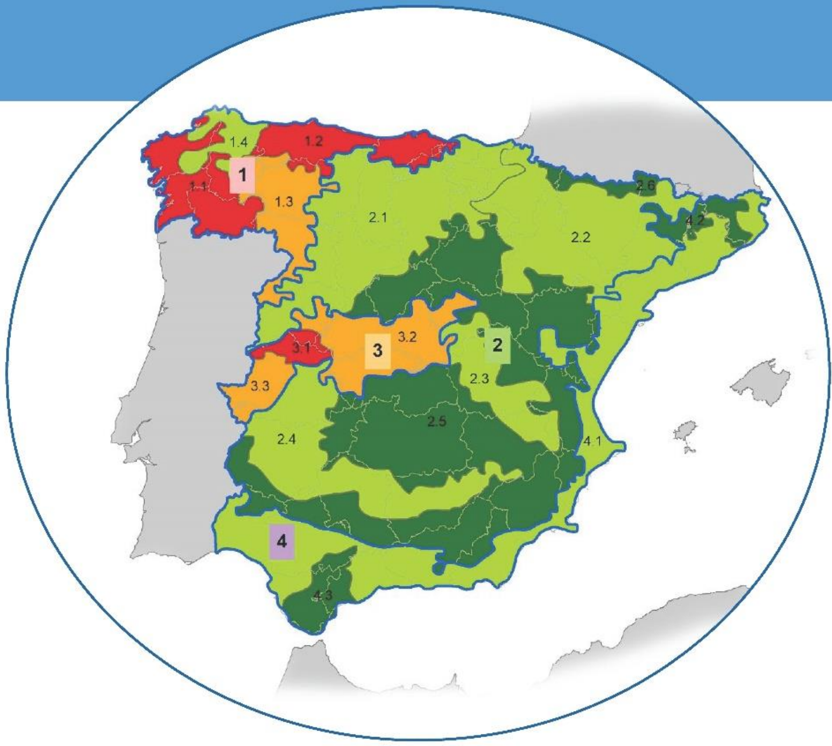
Understanding the contribution of dry periods to forest fire behaviour is a key factor to determine the potential impacts of climate change. Several works suggest that coincident drought conditions and high temperatures promote larger fires, which may experience increased occurrence given the more than likely growth of extreme weather events. However, while analysing relationships between drought and burnt area is a common topic in wildfire science, few works have dealt with their impact in fire occurrence and cause. To explore the influence of drought on wildfires we computed the Standardized Precipitation-Evapotranspiration Index (SPEI), a standard meteorological index that normalizes drought across regions and climates, recommended as a drought indicator by the World Meteorological Organization. SPEI was used to summarize the influence of drought duration (temporal scale of the SPEI calculation) and magnitude (value of SPEI) on fires in Spain. Our main goal was to analyse the relationships between drought, fire frequency (N) and burned area (BA) in different scenarios of fire size (all fires, fires above 1 Ha and fires above 100 Ha) and ignition source (natural, unintended and arson). To do so, we constructed time series of fire activity and SPEI at monthly level. Fire data series (N and BA) were constructed using fire records from the Spanish General Statistics on Wildland Fires database (EGIF). In turn, SPEI was calculated at different time scales (3, 6, 12 and 24 months). Time series were then decomposed into season and trend components and submitted to correlation analysis by means of the Spearman's Rho Rank Correlation test. This procedure was conducted for each combination of temporal component, fire size, ignition source and SPEI level to provide a deep insight into the underlying factors linked to the temporal evolution of fire activity.

Correlation outputs suggest that short-term droughts (SPEI 3 and 6) have more influence in fire occurrence (N) than extended droughts (SPEI 12 and 24), in part because the later are uncommon events. The seasonal cycles of short-term SPEI are highly associated to the occurrence of human-caused (unintended plus arson) large fires (size >100 Ha). Natural fires in the hinterland region of Spain require longer dry conditions, being more correlated to SPEI 6 than SPEI 3, but not going any further (SPEI 12 or 24). Regarding the trend component, which is linked to the overall temporal evolution of forest fires, the larger association is detected between natural fires above 1 Ha and SPEI 3. On the other hand, despite showing high correlation values in some regions, change in accidental and arson fires do not show strong association with SPEI-drought. The affected burnt area (BA) depicts a different spatial pattern. Seasonal cycles of BA seem to be strongly associated to SPEI 24, thus with prolonged dry conditions. This behavior is clearly displayed in the northern half and hinterland of mainland Spain. On the contrary, the trend component of BA is more spatially diverse and dispersed across the territory, with no clear pattern.



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