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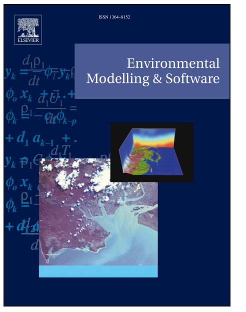

Modelling wildfire occurrence at regional scale from Land Use/Cover and climate change scenarios

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Modelling wildfire occurrence at regional scale from Land Use/Cover and climate change scenarios

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Abstract

Wildfire occurrence is expected to increase in future climate and Land Use Land Cover (LULC) change scenarios, especially in vulnerable areas as the European Mediterranean Basin. In this study future probability of wildfire occurrence was estimated for a 20-year time period (2041-2060, centered on 2050) by applying a statistically-based regression model using LULC-derived contact areas with the forest cover (interfaces) as proxy for the human-related factor and a combination of Live Fuel Moisture Content and seasonal climate-related variables as predictors. Future wildfire occurrence was mapped under RCP 8.5 high emissions scenario in four Spanish regions with heterogeneous socioeconomic, LULC and natural fire-related characteristics at 1 km^2 target spatial resolution. Results showed increased wildfire probability in ~19-73% of 1 km^2 cells, observing regional differences in the variable effects. This approach could be applied to other spatial scales offering tools for planning and management actions and to obtain different possible future scenarios.

Keywords

Land Use Land Cover interfaces, Climate Change Initiative-Land Cover, LFMC, Coupled Model Intercomparison Project 5 (CMIP5), business-as-usual scenario, Wildland Urban Interface

1. Introduction

Nowadays wildfires are one of the significant threats to forested areas worldwide, and the European Mediterranean Basin is one of the more susceptible areas to fire episodes, reporting more than 85% of the total burned area in Europe (San-Miguel-Ayanz et al., 2012). Wildfires, however, are complex phenomena involving multiple factors mediate, e.g. fuel availability, moisture conditions, natural and human ignitions, meteorological/climate drivers

(Gudmundsson et al., 2014) and management decisions (Hély et al., 2001), which also operate at different spatial and temporal scales (Bedia et al., 2015).

Reported changes in the Mediterranean region regarding the use of land and climate (Spinoni et al., 2020) are affecting the fire cycle (Pausas and Fernández-Muñoz, 2012), increasing the frequency and severity of wildland fires (Moreno et al., 2013), and threatening ecosystem stability, the provision of services, habitat and biodiversity conservation, landscape value and aesthetics, as well as property and human lives. These changes are expected to become more intense in the coming century (Syphard et al., 2019), increasing their effects on fires and the consequential impacts on human communities worldwide. Spain is representative of these changes within Mediterranean Europe (Stellmes et al., 2013), as lengthened, and longer fire weather seasons have become more frequent (Jolly et al., 2015). Understanding the past relationships among land use land cover (LULC) changes, climate and wildfire occurrence will allow for the prediction of future impacts and the evaluation of vulnerabilities, which will serve as input for management and policy actions (Gallardo et al., 2015). Resulting relationships will depend on the type and force of driving factors and their importance in different regions.

The European Mediterranean Basin has experienced profound LULC changes derived from human activities (Geri et al., 2010). In the last century, LULC changes in rural areas of Southern European countries were first linked to the intense abandonment of the countryside (1950s-1960s). Then, there was a shift to a new agricultural and mechanized system (1980s), followed by urban expansion in forested areas and increased recreational activities and the consequential intensification of the pressure on natural zones (2000s) (Vilar et al., 2016a). Such abandonment led to exceptional fuel accumulation due to natural reforestation processes (Geri et al., 2010) and urban pressure due to the increase in contact areas between forest and urban constructions (the so-called Wildland Urban Interface or WUI), all of which triggered an increase in wildfire risk. Besides, LULC also creates an impact through the ignition of fires, with more than 80% of fires in this area being linked to human activities and the result of negligence, accidents or acts of arson (Ganteaume et al., 2013), e.g., the use of fire to control herbaceous vegetation for cattle grazing or to clean brushwood in crops (lightning causes ~5% in average of the known fires in this basin). Given the wide range of the human activities effects, several studies include the contact areas between forest and other covers, the so-called interfaces, such as WUI (Vilar et al., 2016a; Chas-Amil et al., 2013; Modugno et al., 2016; Lampin-Maillet et al., 2011), agricultural-forest interface (Gallardo et al., 2015; Martínez et al., 2009; Rodrigues et al., 2016) and grassland-forest interface (Rodrigues, 2014; Vilar et al., 2019), among others as human drivers of wildfire occurrence. Assuming that socioeconomic changes are likely to continue, further changes in LULC are also expected. Projecting the amount of LULC change and the location thereof will allow for future LULC derived interfaces to be obtained and for the human factor of the wildfire occurrence be represented (Gallardo et al., 2015).

On the other hand, the climate role in wildfires is mainly linked to the control of vegetation characteristics and status (Westerling et al., 2011). Pre-fire-season weather conditions have been proved to have a strong influence on the ignition and propagation of large fires because of their effect on fuel load and flammability (Urbieta et al., 2015). Moreover, the fuel moisture content (FMC), defined as the mass of water contained within vegetation per dry mass, is a critical variable affecting fire interactions with fuel (Yebra et al., 2013), and might affect both fuel ignition and fire spread rate (Viegas et al., 1992; Rossa et al., 2017). As FMC increases, the flammability of fuels tends to decrease, as more energy is needed to evaporate water before burning organic tissues (Argañaraz et al., 2018). FMC is usually separated into live (LFMC) and dead fuels (DFMC) (Chuvieco et al., 2004). Most operational fire danger rating systems include the estimation of DFMC, those lying on the forest floor (leaves, branches and debris) (Camia et al., 2003). Still, the estimation of LFMC is included less often. Less significant relations between fire spread or intensity were found in experimental data field analysis for a shrub or conifer forest (Fernandes and Cruz, 2012). Among other reasons, this is because LFMC is the result of complex interactions between previous and concurrent weather and the varied biological mechanisms that influence water content and dry matter accumulation (Jolly et al., 2014; Turner, 1981).

Climate change trends in Southern Europe are expected to lead to increased temperature, a greater number of heatwaves and dryer days (Cramer et al., 2008) and a decreased summer precipitation (Kovats et al., 2014). Modelling studies predict that this will lead to an increase in fire activity (Sousa et al., 2015), the number of large fires (Vázquez de la Cueva et al., 2012) and the burnt area (Amatulli et al., 2013; Turco et al., 2018). Dupuy et al. (2020) recently reviewed 23 studies that projected fire danger indices or fire activity (number of fires, size and burnt area) and at modelled climate-fire relationships in the European context at local, regional or continental scale. Results showed a relative increase (2-4% per decade) in mean seasonal fire danger under pessimistic climate change scenarios in the Mediterranean regions. Burnt areas are projected to increase everywhere in Southern Europe at a rate of 15-25% per decade (Dupuy et al., 2020).

Several simulation scenario studies have combined factors on humans, topography, vegetation and FMC along with climate change conditions as drivers of future wildfires in fire-prone areas worldwide. Examples of variables included in the modelling processes include, housing density (Westerling et al., 2011), distance to populated places (Liu et al., 2012), land use effects (Syphard et al., 2018), distance to roads (Syphard et al., 2019), road density (Liu et al., 2012), WUI and other land cover interfaces (Gallardo et al., 2015), aspect and slope (Westerling et al., 2011), vegetation type (Syphard et al., 2018) and fine fuel moisture content (Liu et al., 2012) . However, in the European context, Dupuy et al. (2020) claimed that one of the sources of uncertainty in future estimations was the lack of information on the influence of human factors on climate-fire relationships. Moreover they affirmed that the influence of FMC should be taken into account and constitutes a possible source of bias for future predictions.

The main aim of this work was to develop an integrated modelling framework at $1km^2$ target resolution to better understand the importance of climate, LFMC and human factors on future spatial and temporal characteristics of wildfire occurrence in different Southern European regions. To that end, the variable effect and distribution of current and future projected probability of wildfires were analyzed in four areas of Spain. These regions were selected as representative of LULC changes and climate conditions in Southern Europe and have different socioeconomic, biophysical and wildfire characteristics. The specific objectives were first, to calibrate statistical-based regression models for wildfire occurrence combining climate, LFMC, topography and LULC interfaces. Secondly, the regression models were applied to the projected LULC and climate variables obtaining the future wildfire probability. The three main research questions addressed are, (1) would wildfire probability increase or decrease in relation to LULC and climate changes? and how?; (2) which variables would be more influential in the different regions?; and (3) could this modelling framework be applied to other scales and areas for planning and management actions?

2. Study sites

This paper covers four Spanish regions: Ourense, Zamora, Madrid and Valencia (Figure 1, Table 1). These regions are representative of the landscape types derived from the different socioeconomic processes affecting Southern Europe in the last decades and the relation thereof to historical fire events and trends, as explained in the Introduction.

More specifically, two of the sites are rural-oriented (Ourense and Zamora in the northwest of Spain), and the other two are representative of urban development (Madrid and Valencia, located in central Spain and on the eastern Mediterranean coast, respectively). The rural-oriented sites have low population densities (Table 1) with regressive demographic dynamics, due to low birth rates and an ageing population (Balsa Barreiro and Hermosilla, 2013, Spanish Statistic Institute -INE- 2019), except in the major cities (Moreno et al., 2014). In Ourense, the population is mostly dispersed (Chas-Amil et al., 2015), and the economy is based on the primary sector (Gonzalez and Pukkala, 2007). On the contrary, urban sites have higher population densities, and their economy is based on the tertiary sector (INE, 2019). In the late 1990s, significant urban growth happened in urbanized areas, such as Madrid, in parallel to decreased agricultural and forest areas (Plata Rocha et al., 2011). Also, there was an intense urbanization process in the Spanish Mediterranean Coast, i.e. the Valencian region, disturbing its natural configuration (Syphard et al., 2018; Barbero-Sierra et al., 2013). The expansion of urban construction continued from 2000 until the outbreak of the global economic crisis in

2008. In rural regions, such as Ourense, afforestation processes due to the abandonment of agricultural activities have continued for the last four decades (Fuentes-Santos et al., 2013). In Zamora, the abandonment of these activities was accompanied by a decrease in the livestock density until the mid-1990s (Moreno et al., 2014).

Land cover is the landscape resulting from these changes. In Ourense (Figure 1a) forest covers prevail (~67% of the total area), while in Zamora (Figure 1b) agriculture is the predominant land cover (~64% of the total area). In Madrid (Figure 1c) and Valencia (Figure 1d), a more balanced spatial distribution of forest and agricultural areas is observed with urban areas being abundant (16% and 6 %, respectively). Other land cover types relevant to fire occurrence, such as pastures and shrublands, occupy a substantial percentage of the total territory of Madrid (~14% pasture lands) and Valencia (~15% shrublands) in comparison to other regions. Climatic conditions are quite diverse in the selected regions, which have a dissimilar influence on fire incidence and the effects on the territory. Ourense has oceanic conditions but warm summers. Zamora and Madrid are representative of Mediterranean continental climate, while Valencia has a Mediterranean climate (Spanish Meteorology Agency, or AEMET, 2019) (Table 1). About wildfire characteristics, differences between the selected regions are notable in terms of the number of fire events and burnt area, as well as fire causes. Ourense had both the highest number of fires and the largest burned area in the last decade 2006-2015, with more than 70% being due to arson (Andrade Otero et al., 2019) and Ministry of Agriculture, Fisheries and Food www.mapa.gob.es). In Ourense site, fires are then explained by other factors that are not climate-related, such as accidents, neglect and acts of arson aimed at transforming the territory (Andrade Otero et al., 2019).

Table 1. Summary of the characteristics of the four study sites regarding the population density (Spanish National Statistics Institute), land cover relevant to fire occurrence (CCI-LC map), average annual temperature and precipitation (AEMET) and fire statistics (Spanish Ministry of Agriculture, Fisheries and Food, MAPA)

			Climate		Fire statistics (2006-2015)		
Site	Density [inhabitants/km^2]	Land cover relevant to fire occurrence [%]	Average annual temperature [ºC]	Average annual precipitation [mm]	Number	Total forested[1] and [wooded] Burned area [ha]	Cause [%, type]
Ourense	~42	~67% forest	10-14	1000	~14653	~120329 [~41933]	~75% arson ~5% accidental ~1% lightning ~11% unknown
Zamora	~17	~64% agricultural	12-14	400-1000	~3570	~47125 [~7148]	~63% arson ~16% accidental ~3% lightning ~1.2% unknown

Madrid	~800	~16% urban ~14% pastures	12-14	400-1000	~2900	~7360 [1207]	~22% arson ~30% accidental ~2.5% lightning ~14% unknown
Valencia	~240	~6% urban ~15% shrublands	13-23	450	~1982	~58760 [23999]	~30% arson ~30%accidental ~11% lightning ~3% unknown

[1] Forested stand for wooded and non-wooded (woody and grassland) vegetation

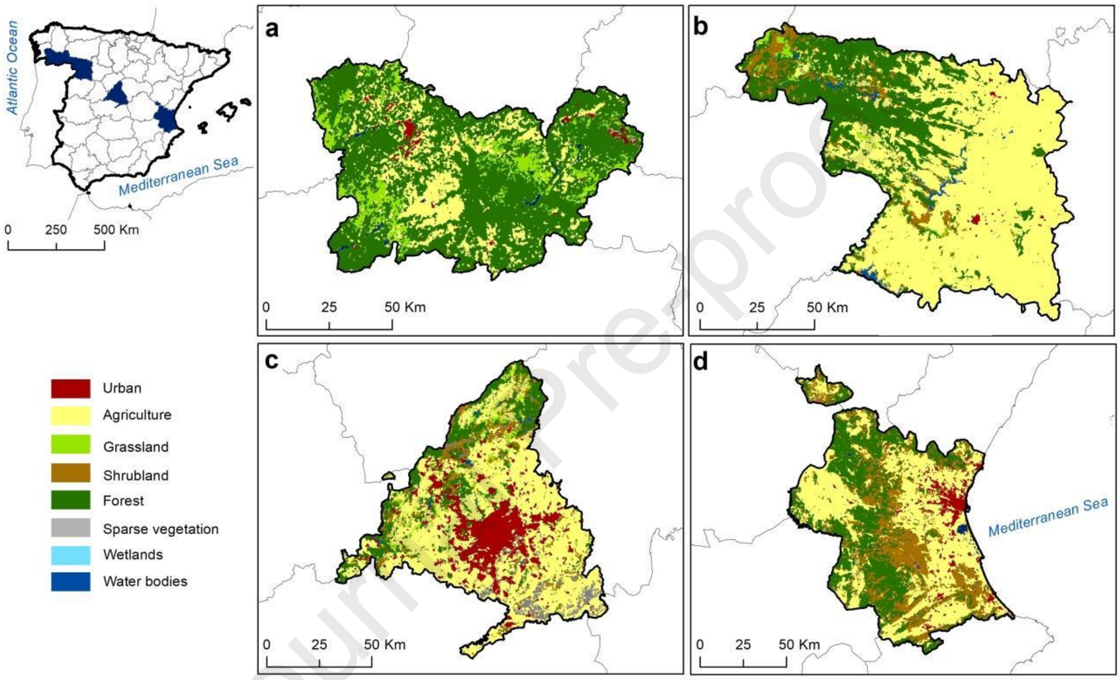

Figure 1. Location of the study regions in Spain: Ourense (a), Zamora (b), Madrid (c) and Valencia (d) and their land covers: according to the Climate Change Initiative-Land Cover, CCI-LC 2005 epoch map (covering 2003-2007) reclassified to the following eight classes: urban, agriculture, grassland, shrubland, forest, sparse vegetation, wetlands and water bodies

3. Methods

The methodological steps followed to obtain the future wildfire occurrence in the study sites for the 20-year time period (2041-2060, centered on 2050) include four main phases: (1) modelling the baseline wildfire occurrence, (2) simulating LULC change scenarios, (3) building climate projections and (4) modelling future wildfire occurrence (Figure 2). This integrated modelling framework was proposed at 1km^2 target resolution as appropriate for regional scale in Spain due to the average size of its regions and the management system organization, as in previous works (Chuvieco et al., 2010, Gallardo et al., 2015, Vilar et al., 2016b). Specific data used for modelling has been generated at this resolution and spatially processed. The period of

1998 to 2015 was used for the baseline wildfire modelling and LULC change simulations. These years represent the specific socioeconomic and land cover changes associated with wildfire occurrence that took place in Spain in the last decades. For modelling the baseline wildfire occurrence (phase 1) a 10-year period (2001-2010) was chosen as it was considered sufficient to gather the fire occurrence and recent climate and LFMC conditions variability. The 1998 and 2008 land cover maps were used to calibrate LULC change scenarios while the 2015 map to perform its assessment (phase 2). Lastly, LULC 2050 projections and 20-year (2041-2060) climate change projections were obtained (phase 3), and wildfire probability was then obtained for that period (phase 4).

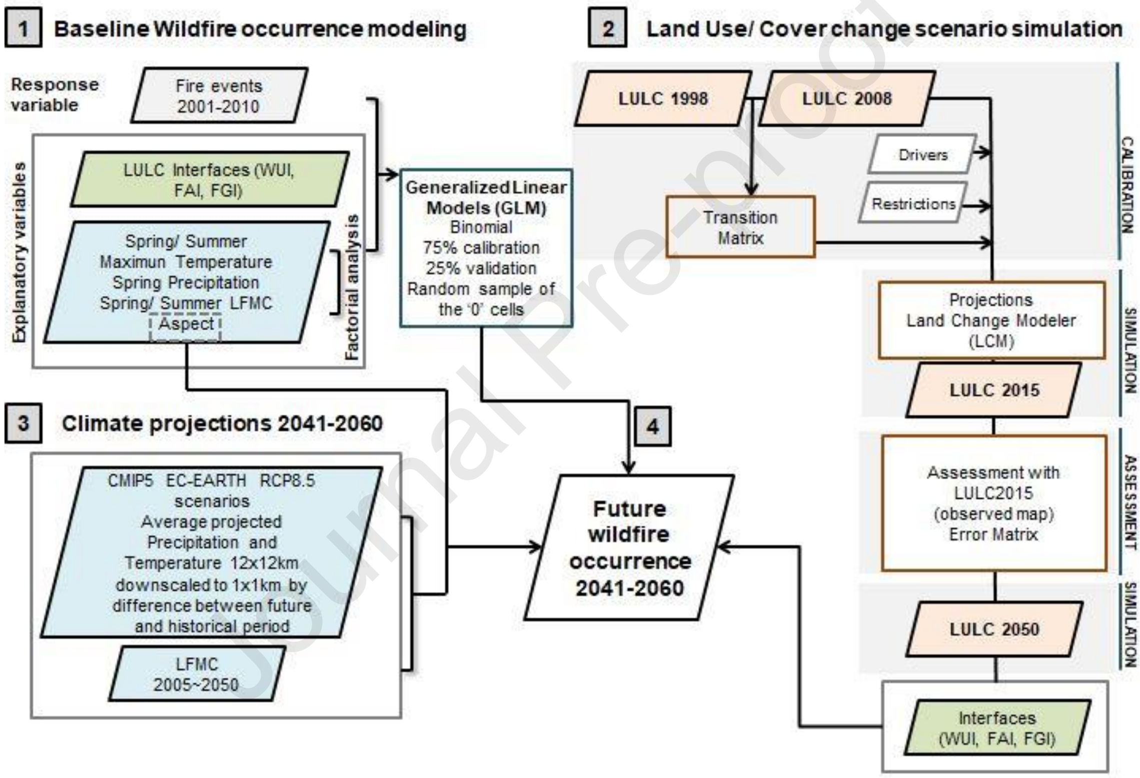

Figure 2. Methodological workflow highlighting the main four phases: (1) modelling the baseline wildfire occurrence, (2) simulating LULC change scenarios, (3) building climate projections and (4) modelling future wildfire occurrence. Parallelograms represent the input and output data (interfaces in green; climate variables, aspect and LFMC in blue; LULC maps in light brown). Rectangles represent applied processes. WUI, FAI and FGI stand for Wildland-Urban, Forest-Agricultural and Forest-Grassland Interfaces, respectively. LFMC stands for Live Fuel Moisture Content.

3.1. Baseline wildfire occurrence modelling

3.1.1. Explanatory variables

Explanatory variables used to model the baseline wildfire occurrence were related to LULC (interfaces), LFMC, climate and topography (aspect) (Table 2).

3.1.1.1. LULC maps and derived Interfaces

The ESA Climate Change Initiative-Land Cover (CCI-LC) map (https://www.esa-landcover-cci.org/) was used to both derive LULC interfaces and to simulate LULC change scenarios. CCI-LC was chosen because of its global availability, fine spatial resolution (300 m), period covered (yearly maps since 1998-present) and its adequacy for estimating wildfire occurrence at local and European scales (Vilar et al., 2019). This product includes 22 land cover classes using United Nations Land Cover Classification System (UN-LCCS) (Di Gregorio et al., 2016). Taking into consideration the thematic meaning of the land cover in relation to wildfire occurrence analysis, the original CCI-LC legend was aggregated into eight classes (urban, agriculture, grassland, shrubland, forest, sparse vegetation and bare areas, wetland, and water bodies, to obtain a more manageable number of classes (Figure 1).

Three LULC interfaces were obtained and used as proxies for the role of human activity in wildfire occurrence: (1) Forest-Agricultural Interface (FAI) includes the interfaces between forest, grassland, shrubland and agricultural; (2) Forest- Grassland Interface (FGI) consists of the interfaces between forest, shrubland and agricultural and (3) Wildland-Urban Interface (WUI) consists of the interfaces between forest, grassland, shrubland and urban. Specifically, FAI represented those areas where a fire is used to carry out agricultural activities, such as harvest elimination or brushwood clearing on the borders of the croplands that might spread to nearby forest areas (Gallardo et al., 2015). FGI denoted areas where cattle grazing and other activities, such as pasture burning to regenerate the herbaceous vegetation layer, might ignite a fire and affect adjacent forest areas. Finally, WUI represented the urban development that has happened close to the natural areas and thus the human pressure on the forest areas via activities that might also ignite a fire (e.g. brush cleaning close to the houses, gardening works, recreational activities as barbeques, etc.). The interfaces were defined as 1 pixel (300x300m) to both sides of the contact between the uses defined for each interface type. Then, those pixels were overlaid to the 1x1 km target resolution grid. The area occupied by the interface pixels by grid unit was divided by $1km^2$. Then, density values by cell of each interface type were obtained. This more general interface delineation and its calculation method allowed its obtainment in the future LULC projection maps.

3.1.1.2. Live Fuel Moisture Content (LFMC)

LFMC was obtained using a physically-based inversion model based on MODIS reflectance data (500 m Nadir BDRF-Adjusted reflectance product, MCD43A4 Collection 6) (Yebra et al., 2018). Three land cover classes were taken into consideration due to their differences in structural characteristics and biochemical composition and accordingly, three Lookup Tables were simulated using different radiative transfer models (RTMs): grasslands (Jurdao et al., 2013a; Yebra et al., 2008), shrublands (Jurdao et al., 2013a; Yebra and Chuvieco, 2009) and forest (Jurdao et al., 2013b). Simulated spectra were compared by a merit function with the observed spectra from MODIS images (see Yebra et al., 2018, for further details).

Due to the strong seasonality of wildfire occurrence in Spain (Andrade Otero et al., 2019), months were grouped into spring (March to May) and summer (June to September) seasons. Monthly average LFMC for spring and summer was then extracted and calculated for each year of the analyzed period (2001-2010) to take into consideration the inter-annual variation within the period. Spring and summer LFMC yearly values were then overlaid to the 1 km^2 grid cell resolution.

3.1.1.3. Climate data

Spring accumulated precipitation and spring and summer maximum temperature were the climate-related seasonal variables for modelling. These three variables were computed as the monthly average for each year of the 2001-2010 study period, to take the inter-annual variation within the period into consideration.

For Zamora and Madrid, a 1 km^2 high-resolution gridded dataset (MG-UC) was built following the two-step regression kriging (Hengl et al., 2007) interpolation method described in Bedia et al. (2013). This method uses several orographic variables, including elevation, distance to the coastline and topographic blocking effects as predictors to reach the target resolution. This process was based on a quality-controlled weather stations network – 2858 and 1158 stations of daily precipitation and temperatures, respectively, for Castilla y León (Zamora) and 384 and 144 stations of daily precipitation and temperatures, respectively, for Madrid- belonging to the Spanish Meteorology Agency (AEMET).

In Ourense and Valencia, due to the lower weather station density, the recently developed SAFRAN (*Système d'Analyse Fournissant des Renseignements Atmosphériques à la Neige*) meteorological analysis system (Durand et al., 1993; Durand et al., 1999) available for Spain (Quintana-Seguí, 2015) was used. This dataset is based on a high-density network of meteorological stations operated from the AEMET and covers 35 years (1979/1980-2013/2014) at 5 km^2 grid cell resolution. SAFRAN data was overlaid to the 1 km^2 grid cell resolution chosen for our analysis.

Table 2. Explanatory variables used for baseline wildfire occurrence modelling (2001-2010)

Variable name, *abbreviation*	Description	Scale/resolution	Source	Year/period
Forest Agricultural Interface, *FAI*	Contact areas between Agricultural areas and Forest	300 m	ESA Climate Change Initiative-Land Cover (CCI-LC)	2005 epoch
Forest Grassland	Contact areas	300 m		

Interface, *FGI*	between Grassland and Forest			
Wildland Urban Interface, *WUI*	Contact areas between Settlement and Forest	300 m		
spring accumulated precipitation, *springppt*	Interpolated monthly accumulated precipitation (mm)	1 km/5 km	MG-UC/SAFRAN	Monthly averages in 2001-2010 period
Spring/summer maximum temperature, *springtmax* *summertmax*	Interpolated spring and summer monthly maximum temperature (ºC)	1 km/5 km	MG-UC/SAFRAN	Monthly averages in 2001-2010 period
Live Fuel Moisture Content, *springLFMC* *summerLFMC*	Spring and summer monthly average	500 m	Yebra et al. (2018)	Monthly averages in 2001-2010 period
Aspect, *aspect*	Aspect from the Digital Elevation Model	200 m	Spanish National Geographic Institute (IGN)	

3.1.2. Response variable

Wildfire occurrence modelling relies on the existence of accurate geo-referenced information on fire ignition points. This information is not frequently available. Consequently, the location of fire occurrence based on fire perimeters is used as an alternative. In this study, the most accurate fire data available for each region were used. For Zamora, Madrid and Valencia fire ignition points (x, y coordinates) collected by the regional fire services were available. However, the methodology used to identify and geolocate the fires is not consistent and can vary both spatially and temporally from ground or airborne GPS. Time series available and the number of observations also differ 2007-2010 (1093 observations), 2005-2010 (1449 observations) and 2001-2010 (3713 observations) for Zamora, Madrid and Valencia, respectively. A pre-processing of the different datasets was made to filter errors (i.e., fire ignitions located in water bodies) and to homogenize the information, as well as to analyze the variability of the data. For modelling purposes, fire ignitions (observations) were considered presence or absence and overlaid to the 1 km^2 reference grid cell . For those datasets where the fire cause was available, only human-caused fires and an equivalent proportion of fires with unknown causes were included for the analysis. Fire ignition points were not available from the regional service in Ourense. Consequently, the response variable was generated by combining two satellite products (1) MODIS Terra and Aqua Burned Area (BA) MCD64A1 product, which is a global and monthly gridded 500 m resolution product (Giglio and Justice, 2015) and (2) daily MODIS Hotspots (HS) from MCD14DL and the Visible Infrared Imaging Radiometer Suite (VIIIRS) 375 m (VNP14IMGTDL_NRT) (Giglio et al., 2003). BA was downloaded from

LP-DAAC NASA Land Products and Services (https://lpdaac.usgs.gov/dataset_discovery/modis/modis_products_table/mcd64a1_v006) and HS from Active Fire Data (https://firms.modaps.eosdis.nasa.gov) for 2001-2010. By combining this data, three situations were possible: (1) BA with no HS, (2) HS with no BA and (3) concurrent BA and HS (Figure 3). In (1), the presence (ignition) of a fire was assigned to the 1 km^2 occupied by a larger area of the BA. In (2), a 400 m spatial distance analysis grouped HS and then the one with the earliest date was selected as the ignition of that fire. And in (3) it was considered another ignition by choosing the earlier HS date and time.

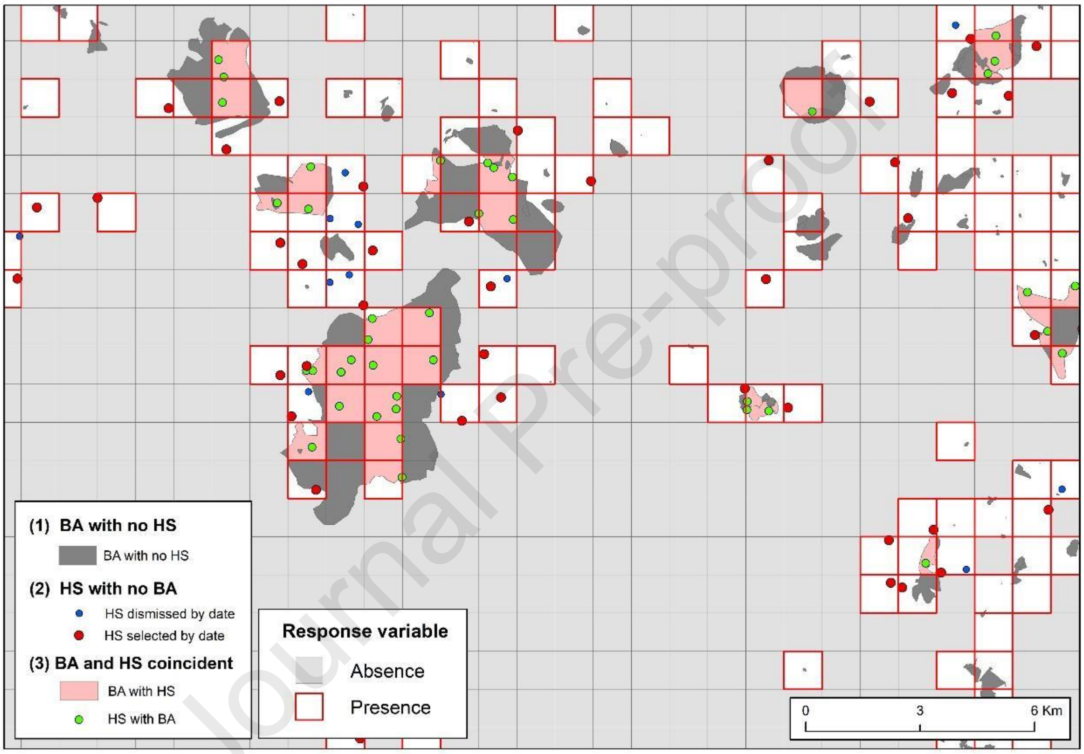

Figure 3. Spatial procedure applied for assigning fire ignition to each cell and thus obtaining the response variable by using BA (Burned Area) and HS (Hotspots) from MODIS exemplified in Ourense site. The combination of BA and HS has led to three possible situations: (1) BA with no HS, (2) HS with no BA and (3) concurrent BA and HS. Where BA was not concurrent with HS (case 1, dark grey) it was calculated the area per cell of the same fire. The ignition of that fire was assigned to the largest area. Where HS was not concurrent with BA (case 2), an exploratory distance analysis was first performed within the points, integrating groups of HS within 400 m distance from each other (considered a single fire) and then selected the HS pixel with the earliest date and time as the origin of that fire (red points). In case BA and HS were concurrent (case 3, pink polygons or green points) it was considered as another ignition. Then, the selected 1 km^2 presence was the one with the earliest date.

3.1.3. Statistical analysis

Wildfire occurrence for the 2001-2010 baseline period was estimated using Generalized Linear Models (GLMs). GLMs are extensions of linear regression models that support response variables with non-normal distributions, such as binomials (Guisan et al., 2002). Binary GLMs are commonly applied to explain the probability of fire occurrence, (Martínez et al., 2009; Rodrigues, 2014; Vilar et al., 2016b). Fire ignitions were used as the response variable, indicating the presence or absence of a fire. Climate-related and LFMC variables were used as predictors. The generalized linear model function available in the GLM package (stats version 3.6.0) for R (RCoreTeam, 2019) with family binomial and logit link (corresponding to logistic regression configuration) was used. Collinearity diagnostics, such as Spearman correlations and variance inflation factor (VIF), were conducted to check whether the explanatory variables were correlated. To alleviate the multicollinearity problem and reduce the dimensionality and complexity of the GLM a factor analysis (Tinsley and Brown, 2000) was fitted using the *factor* function available in the R base package (version 3.6.0). Five components and a non-rotated matrix were chosen.

Modelling wildfire occurrence faces an additional issue related to the response variable. Wildfires are rare events and, therefore, the number of cells with fire absence greatly outnumbered cells with fire presence. Following Preisler et al. (2004) a random sample of the absence-fire cells was selected as model input to solve this problem and retain enough covariate information on the non-ignitions for modelling. This approach introduces a deterministic offset term of –log (π_{xyt}) that does not bias the analysis (Vilar et al., 2010). π_{xyt} denotes the response-specific sampling rate. When N_{xyt}=1, π_{xyt} is also 1 and when N_{xyt} =0, π_{xyt} =π. In this study, a sample of 10% of the zero-fire cells was selected. The resulting dataset was randomly divided into two groups: 75% for model calibration and 25% for validation. The lowest Akaike's Information Criterion (AIC) value was used to select the best model. Predictions were finally obtained for the whole dataset, thus getting the probability of wildfire occurrence for each cell. From the analysis, we obtained the value of Exp (β), the odds ratio, which is the predicted change in odds for a unit increase in the corresponding independent variable (Garson, 2012). Explanatory variables with an odds ratio equal to or greater than 1 meant odds increased and values less than 1 represented a decrease.

3.2. Future wildfire occurrence modelling

3.2.1. LULC scenarios

3.2.1.1. Input data

CCI-LC maps from 1998, 2008 and 2015 were used for the simulation of land cover change scenario. A business-as-usual (BAU) or trend scenario was applied to obtain a LULC map for 2050 using a set of variables representing accessibility, suitability and restrictions behind LULC changes (Table 3). Accessibility, one of the most critical factors leading changes in LULC (Verburg et al., 2004), was represented by the distance to roads and travel costs. The model assumed that people preferred to live close to transport networks, like roads, to minimize their travel time to and from work (Gallardo et al., 2015). About suitability, several variables might give rise to LULC changes. For example, elevation influences vegetation distribution and slope, which affects harvesting practices (Nguyen et al., 2015). Also, lithology controls soil types, given that the kind of soil is considered an essential factor for land abandonment as are the climate conditions (Lasanta et al., 2017). Potential vegetation maps provided information on incentives for the location of natural vegetation covers. Additionally, information about natural protected areas and specific legislation for urban planning can restrict or promote the establishment of certain LULC types (Gallardo et al., 2015). Legal-type restrictions are binding and should be followed by the territory's planners and stakeholders. Moreover, burned areas are also under specific legal regulations, which prevent changes in forest use for 30 years after a fire (Mountain Area Act 43/2003).

Table 3. Driving factors and variables referring to restrictions and incentives used in LULC scenarios

		Description	Scale/resolution	Source
Driving factors				
Accessibility	Distance to roads (primary and secondary)	Euclidean distance	1:200 000	BCN200[1] Spanish Geographic Institute
	Accessibility to roads (main and secondary)	Travel cost	1:200 000	BCN200 Spanish Geographic Institute
	Distance to urban areas	Euclidean distance	1:200 000	BCN200 Spanish Geographic Institute
Suitability	Elevation	Derived from Digital Elevation Model (DEM) 25	25 m	Spanish Geographic Institute
	Slope	Derived from DEM 25	25 m	Spanish Geographic Institute
	Aspect	Derived from DEM 25	25 m	Spanish Geographic Institute
	Soil type	ESDAC-European Soil Database. FAO classification level 1	1 km	ESDAC-European Soil Database (Panagos et al., 2012)
	Lithology	Spanish geological map 2º series (MAGNA50)	1:50 000	Geological and Mining Institute of Spain
	Potential vegetation	Spanish Vegetation series map	1:400 000	(Rivas-Martínez,

				1987)
	Average temperature	30-year monthly average temperature	5 km	SAFRAN
	Average precipitation	30-year monthly average precipitation	5 km	SAFRAN
	Distance to rivers and reservoirs	Euclidean distance		Spanish Geographic Institute
Restrictions				
	Natural Protected Areas	Protected woodlands, Natura 2000 areas, sites of community importance and special protection areas	1:50 000	BDN[2] Spanish Ministry for Ecological Transition and Demographic Challenge
	Zones with legal restrictions to urban growth	Public river domain areas, military zones, airports, road domain areas and restricted natural protected areas		BDN Spanish Ministry for Ecological Transition and Demographic Challenge -BCN200 Spanish Geographic Institute
	Burned areas	Maps of fire perimeters	>40ha	EFFIS European Forest Fire Information System

[1] CN200 stands for National Cartographic Base 1:200 000 scale

[2] BDN stands for Spanish Nature Database 1:50 000 scale

3.2.1.2. LULC 2050 scenario simulation

A future 2050 LULC BAU scenario was run by using the Land Change Modeler (LCM) (Eastman and Toledano, 2018). LCM is a constrained LULC model integrated into Terrset (https://clarklabs.org/terrset/land-change-modeler/). In LCM, the evaluation of the potential of change is empirically obtained through three possible methods: neural networks, logistic regression and a machine learning algorithm. The change allocation is performed through a multi-objective allocation procedure, and the quantity of change is estimated using a Markov matrix (García-Álvarez et al., 2019).

CCI-LC maps from 1998 and 2008 were used to analyze past land cover changes for model calibration. This sequence was taken as a baseline and then simulated to 2015 and compared to the real map for 2015 for validation purposes. The BAU shows what would happen if the historical trends of 1998-2008-2015 were to continue until 2050. Multi-layer Perceptron (MLP) neural network was used to relate LULC and drivers of change (Table 3). For the simulation, the pixels of each LULC class were randomly divided between training (50%) and testing samples (50%). Testing samples allowed for the results to be validated. Models were run several times to reach accuracy rates greater than 50% for each transition. A Cramer's V test (Cramér, 1946) was applied to the set of drivers of change to analyze multicollinearity issues among variables. The expected quantity of change and competitive land allocation based on the 1998-2008 maps sequence for a future date (2015 in this study) was estimated using a Markov matrix. This calibration process compared the number of pixels and the spatial location of each LULC class in both maps. After discrepancy was checked, the model was run up to 2050, obtaining LULC simulated maps for the four sites.

3.2.2. Climate change scenarios

The average projected precipitation and temperature for each year of the 20-year time period (2041-2060) were obtained from the regional climate change projections for Spain developed in the second phase of the National Plan for Climate Change Adaptation 'Escenarios PNACC-2017' (http://escenarios.adaptecca.es). In particular, we have considered the simulation corresponding to the regional climate model KNMI-RACMO22E-v1 driven by the global climate model ICHEC-EC-EARTH-r1i1p1 from the European branch of the Coordinated Regional Downscaling Experiment (CORDEX: https://cordex.org/) (Giorgi et al., 2009, Jacob et al., 2014). In particular, the EUR-11 CORDEX domain was used. Finally, the business as usual RCP 8.5. experiment was used in order to maintain the coherence between the different components. Note that this regional model has shown good performance over the Iberian Peninsula (Kotlarsky et al. 2019; Herrera et al. 2020). To obtain the future climatology at 1 km^2 spatial resolution grid required for the fire occurrence model, the climate change signal (~12 km), defined as the difference between the future (2041-2060) and historical (1981-2010) periods (delta method), was added to the observed climatology (~1 km) (Räisänen, 2007; Zahn and von Storch, 2010; Bedia et al., 2013):

$$delta = future - historical \rightarrow projection = climatology + delta$$

Note that this is the simplest bias calibration method, as it assumes an additive constant bias (***b***) of the model which is removed when those deltas are considered:

$$delta = future - historical = (future + \boldsymbol{b}) - (historical + \boldsymbol{b})$$

The interannual variability of the climatic variables was evaluated through T-Test (equal means) and F-Test (equal variances) comparing each year from 2041 to 2060 with 2050 (centered year of the period where LULC projections were calculated). In order to ensure the coherence, at least up to some point, between the different layers included in the model along the whole period.

3.2.3. LFMC prediction

Due to the absence of future LFMC projections, a comparison between present and future climate conditions was carried out. LFMC interacts with rainfall, air temperature or soil moisture (Qi et al., 2012; Dennison and Moritz, 2009) so the purpose of this comparison was to identify the year within the study period (2001-2010) most similar to year 2050 (center of the 20-year period from 2041 to 2060) in terms of climatic conditions and to use its LFMC as the values for 2050. To this end, the Euclidean distance between the present and future spatial patterns of spring precipitation and spring and summer maximum temperatures was obtained for each year of the 2001-2010 study period considering the four regions together. The distance was obtained considering each variable independently and their joint standardized version.

3.2.4. Statistical model for future wildfire occurrence

Future wildfire occurrence was obtained by applying the historical GLM model for each study site using input data (LULC maps, climate data and LFMC) projected up to the 20-year time period (2041-2060, centered on 2050). The factor analysis representing the climate and LFMC variables were translated into the coefficients thereof to be applied to this new dataset using the following relationship:

$$F_i = U_{i,1} \times X_1 + U_{i,2} \times X_{i,2} \ldots \ldots + U_{i,k} \times X_k \quad (2)$$

where $F_i$is the i-*th* factor scores, $U_{i,j}$ are the components of the eigenvectors. Then, the model can be expressed as:

$$B_1 \times \left(U_{1,1} \times X_1 + U_{1,2} \times X_{1,2} \ldots \ldots + U_{1,k} \times X_k\right) + \ldots + \quad (3)$$

$$B_k \times \left(U_{k,1} \times X_1 + U_{k,2} \times X_{k,2} \ldots \ldots + U_{k,k} \times X_k\right)$$

Thus, the future model is as follows:

$$X_j \times \sum_{i=1}^{K} \quad B_i \times U_{i,j} \quad (4)$$

Projected probability values were obtained for each year from 2041 to 2060. Moreover, the mean and the standard deviation of these probability values of the 20 years of the period were calculated to explore the projected values and its uncertainty. Maps of 20-year (2041-2060) wildfire occurrence probability were finally obtained for each study site at 1 km^2 target resolution.

4. Results

4.1. Baseline wildfire occurrence

4.1.1. Explanatory and response variables

Figure 4 shows the LULC interfaces derived from CCI-LC 2005. The extent and spatial distribution differed among sites. *FAI* dominated in all regions. *FGI* presence was also notable in Ourense (Figure 4a). Cells covered by *WUI* were also crucial in all study sites except Zamora (Figure 4b).

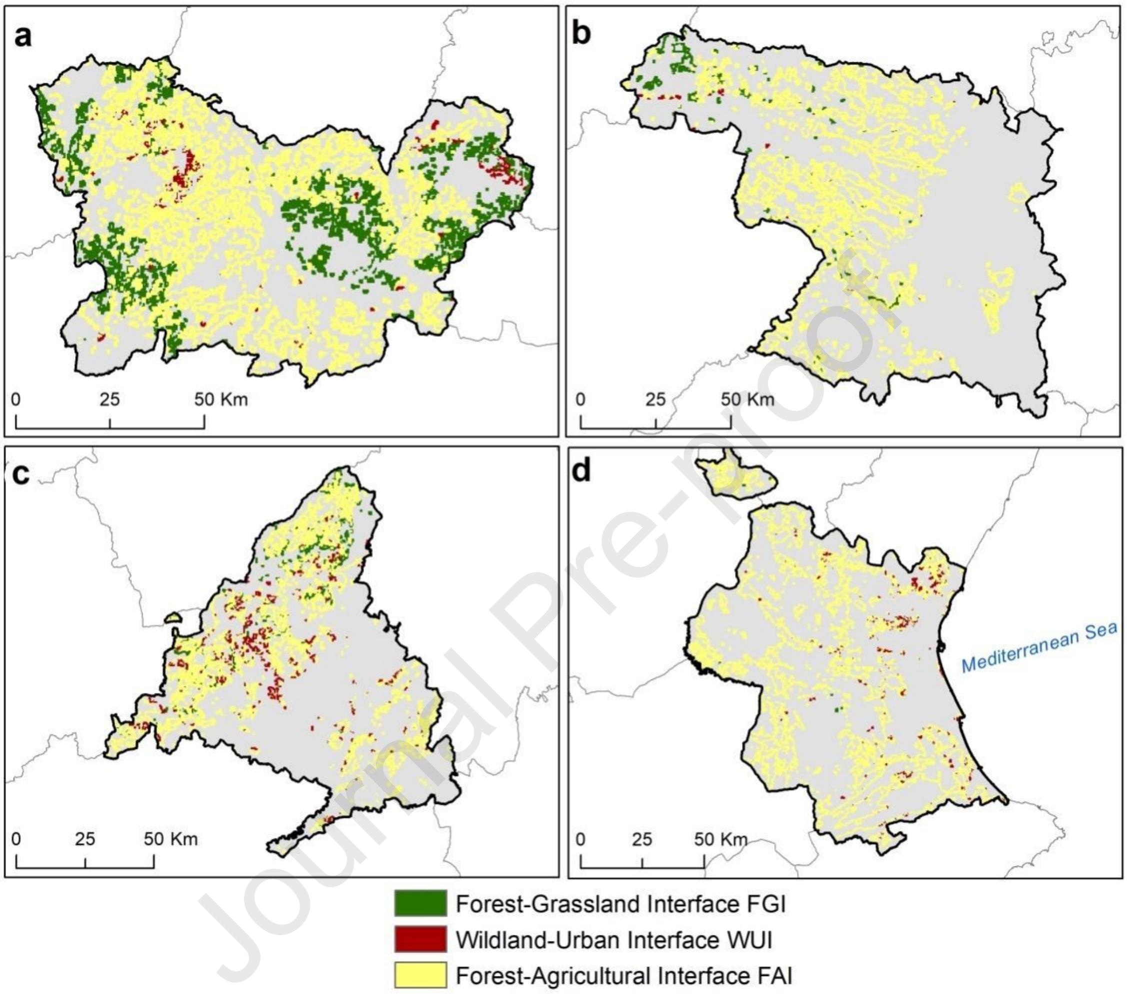

Figure 4. Baseline 2001-2010 LULC Interfaces: FGI (Forest-Grassland), WUI (Wildland-Urban) and FAI (Forest-Agricultural) from CCI-LC 2005 in Ourense (a), Zamora (b), Madrid (c) and Valencia (d).

Seasonal climate-related variables within the baseline modelling for the 2001-2010 period included for the factor analysis showed differences among the years of the study period, illustrating then the expected variability. There were also differences among the regions, corresponding to differences in the base climate conditions used (Figures A.1, A.2 and A.3). For Zamora and Madrid data at 1 km^2 grid resolution were calculated through downscaling processes explained in Section 3.1.1. In contrast, for Ourense and Valencia SAFRAN database was downscaled from 5 km^2 to 1 km^2 grid resolution.

Spring and summer LFMC also showed differences over the 2001-2010 period among the regions and within them in the space (Figure A.4).

Figure 5 shows the wildfire occurrence maps for the study sites as presence/absence of the ignition of a fire (response variable).

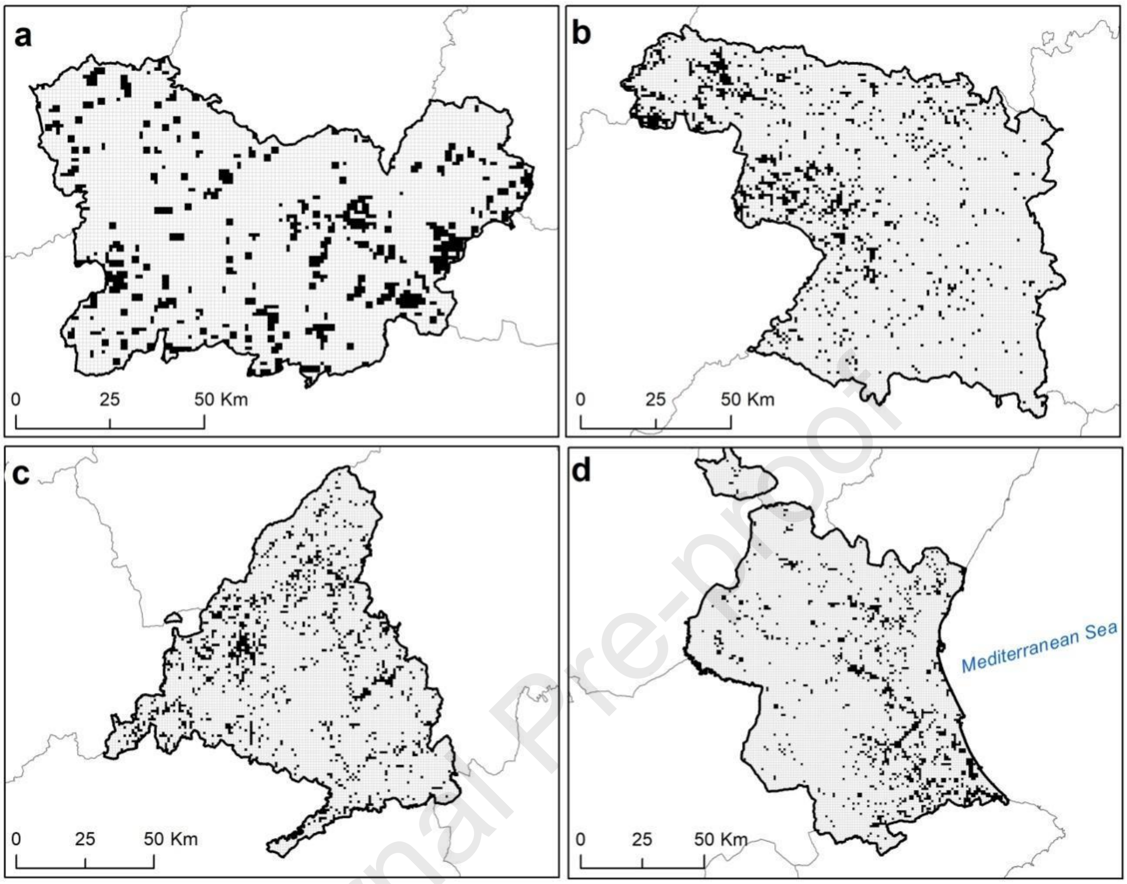

Figure 5. Wildfire occurrence maps for the baseline wildfire occurrence modelling. Response variable (wildfire ignitions) presence (marked in black) absence in 1 km^2 grid cells for Ourense (a), Zamora (b), Madrid (c) and Valencia (d)

4.1.2. Modelled wildfire occurrence

The first three factors explained more than 80% of the variance in all sites (Table 4). The first factor was positively and strongly related with spring and summer maximum temperature in all sites except for Valencia, where the effect was also positive but with lesser influence. Spring LFMC presented stronger effect followed by summer LFMC. The second factor was determined by LFMC (spring LFMC in Zamora and Madrid, summer LFMC in Ourense) but with a weaker effect in the Valencian site, where spring maximum temperature had a more significant impact. Finally, the third factor was determined either by spring precipitation (Ourense and Valencia) or summer LFMC (Zamora and Madrid).

Table 4. Factor scores from inter-annual (2001-2010) factor analysis of climate variables and LFMC. Shaded grey showed the highest correlation values between the variables

	Factors and score coefficients

Study sites	Variable	1	2	3
Ourense	*Spring LFMC*	0.394	0.818	0.000
	summer LFMC	0.294	0.849	-0.142
	spring ppt	-0.221	0.204	0.940
	spring tmax	0.877	-0.351	-0.085
	summer tmax	0.836	-0.262	0.388
Zamora	*spring LFMC*	0.198	0.839	-0.507
	summer LFMC	-0.428	0.605	0.667
	spring ppt	-0.787	0.017	-0.059
	spring tmax	0.903	0.071	0.190
	summer tmax	0.865	0.049	0.193
Madrid	*spring LFMC*	-0.181	0.859	0.418
	summer LFMC	-0.471	0.533	-0.670
	spring ppt	-0.720	-0.034	0.394
	spring tmax	0.937	0.188	-0.008
	summer tmax	0.909	0.226	0.057
Valencia	*spring LFMC*	0.849	0.403	-0.101
	summer LFMC	0.827	0.453	-0.059
	spring ppt	-0.246	0.691	0.632
	spring tmax	0.380	-0.707	0.094
	summer tmax	0.483	-0.575	0.527

LULC interfaces, aspect and the obtained climate-LFMC factors were included as variables to model baseline wildfire occurrence (Table 5).

Table 5. Estimated and significant GLM regression coefficients by study site resulting for the modelling by using LULC interfaces, aspect and Factors as independent variables. Standardized LULC interfaces are represented by *z*. Exp(β) stands for exponentiated coefficients: the odds a wildfire occurs.

	Estimated coefficient (β) [Exp (β)]			
	Ourense	Zamora	Madrid	Valencia
(Intercept)	-4.239	-4.350	-3.388	-4.519
zFAI	-	0.358 [1.431]	0.241 [1.272]	0.388 [1.474]
zWUI	-	0.129 [1.138]	0.262 [1.299]	0.210 [1.234]
zFGI	0.388	-	-	-

	[1.475]			
aspect	-	-	-	-
FACTOR1	-0.560 [0.570]	-0.359 [0.698]	0.190 [1.210]	0.738 [2.092]
FACTOR2	-	-0.237 [0.788]	0.406 [1.502]	0.287 [1.333]
FACTOR3	-0.129 [0.878]	0.561 [1.753]	-	-0.123 [0.883]

The significant selected variables varied by each site. *Aspect* was not significant in any of the studied sites. *zFGI* was only significant in Ourense. The other two LULC (standardized) interfaces, *zFAI* and *zWUI,* were significant for all sites except for Ourense, where *zFGI* was of importance. The exponentiated coefficient values (Exp (β)) indicated the effect on the increase of a wildfire occurrence. For example, the Exp (β)= 1.475 shown in *zFGI* for Ourense indicated that for a one-unit increase in *zFGI* in Ourense and where the other variables remained constant, the probability of a wildfire multiplied by 1.47 (an increase in the odds of a wildfire occurring of about 47%). In all sites, LULC interfaces had Exp (β) values that were greater than 1 (meaning an increase in the odds). *zFGI* was the most influential variable in Ourense and *zWUI* and *zFAI* were second most important in Madrid, Valencia and Zamora. The significance and effects of the combined LFMC and climate-related variables (*FACTOR* variables) differed depending on the site. For Madrid and Valencia, the factor mainly determined by the maximum temperature in spring or summer increased the probability of wildfire occurrence (where the other variables remained constant). On the contrary, a decrease in the odds of a wildfire occurrence (Exp (β) < 1) was due to the factor mainly determined by the spring precipitation in Ourense and Valencia and by LFMC (mostly spring) in Zamora. However, maximum temperature determined the factor in two sites (Ourense and Zamora), decreasing the probability of a wildfire. In contrast, the factor determined by LFMC increased the odds of a wildfire (Madrid and Valencia).

There were differences in the spatial distribution of the predicted probabilities within each of the sites (Figure 6). However, probability distribution values were similar except for Madrid (Figure 6c), where medium values covered most of the site.

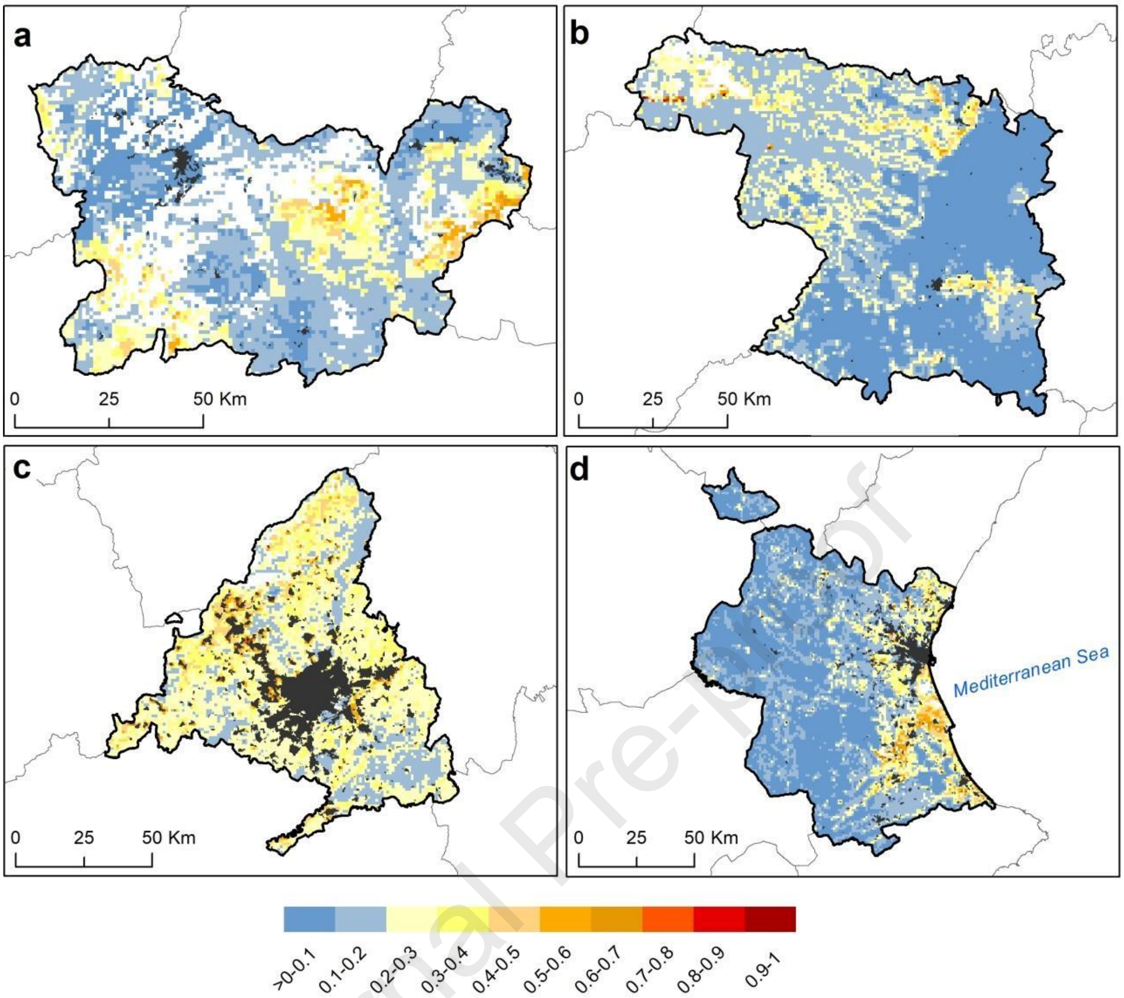

Figure 6. Baseline (2001-2010) probability of wildfire occurrence by 1 km^2 grid cells for Ourense (a), Zamora (b), Madrid (c) and Valencia (d). Settlement areas are displayed in dark grey (CCI-LC 2005 source). White cells represent null values. Medium probability values prevailed in Madrid (c). The highest probability values were mainly located in southwestern and northeastern areas, as well as in a centrally located patch in Ourense (a). The highest wildfire probability areas mostly covered the western in Zamora as well as a patch in the central south (b). In Valencia (d), a wildfire was more probable in areas located in an eastern fringe running north to south along the coast.

4.2. Future wildfire occurrence

4.2.1. LULC scenarios and derived interfaces 2050

LULC BAU scenarios were assessed during the calibration processes by comparing the 2015 predicted map with the actual 2015 map. For all study sites, the total agreement was ~96%. Looking at the results by class, agricultural and forest classes presented the greatest accuracy (>90%) while errors of commission and omission differed for each site. In general, LULC classes were adequately predicted except for the urban class, which presented both errors of omission (27% and 12% for Zamora and Madrid, respectively) and commission (46%, 17% and 23% in Zamora, Madrid and Valencia, respectively). Agriculture in Ourense site had an error of commission of ~13%.

BAU scenarios showed if the trends in LULC changes continued as observed between 1998 and 2008. The more settled, urban sites (Madrid and Valencia) experienced urban development nearby the large cities (peri-urban areas), road networks and along the coast in the case of Valencia. Great road accessibility due to high road density in these areas played a role in projected urban development. Urban grew 27% and 73% in Madrid and Valencia, respectively. Land abandonment was reflected in these sites in the decreased percentage of agriculture (50% and 14% decreases, respectively), where were mainly replaced by urban. Both in Madrid and in Valencia, shrubland decreased and in Valencia shrubland were converted into forest (encroachment process). Forest class increased to 60%, but the greatest increase was notably in the grassland (>100%) in both sites, too. On the other hand, in the more rural-oriented sites (Zamora and Ourense), the LULC tendency showed two different situations. In Zamora, land abandonment was reflected in the decreased agriculture class (22%) and increased shrubland and grassland (20% and 73%, respectively). Agriculture was replaced by forest lands. However, in Ourense, the tendency showed an increase in an agriculture class, which continued in the projected LULC 2050 map, being 58% larger. In this site there will be less forest and mostly shrubland classes. Forestlands will be replaced by agriculture and there will be an increase in the urban areas nearby the existing ones. The maps of changes between real 2015 and simulated 2050 maps are available in the supplementary material (Figure A.5).

LULC 2050 simulated maps controlled the changes in the extension and location of the 2050 LULC interfaces. Foreseen growth in grassland class in three sites (Madrid, Zamora and Valencia) notably increased *FGI* (Table 6). In Madrid, the projected growth in settlement class also increased *WUI* (17%), but not in the case of Valencia where *WUI* decreased by 56%. Even if projected forest lands increased in Valencia, shrubland declined, and this class belonged to forest class when calculating LULC interfaces (see Section 3.1.1). A lesser amount of shrubland influenced the reduced contact between urban areas and forest in this site. The reduction in projected agriculture class affected the decrease of *FAI* in all sites, even in Ourense but to a lesser extent.

Table 6. Percentage of change in LULC interfaces between 2005 and projected 2050 by study site. Decreases are highlighted in light grey

	Ourense	Zamora	Madrid	Valencia
FAI	↓13%	↓26%	↓46%	↓32%
WUI	↓78%	↓35%	↑17%	↓56%
FGI	↓27%	↑73%	↑>100%	↑>100%

4.2.2. Climate change scenarios and projected LFMC

Climate variables (precipitation and maximum temperature) were projected to the 20-year time period (2041-2060) to the 1 km^2 target. Then, spring precipitation, spring and summer maximum temperature were extracted. The interannual variability of the climatic variables showed significant differences among years, but retained the spatial pattern and gradients which were important due to their interaction with the rest of the variables (interfaces, aspect and LFMC). Spring precipitation decreased in 2041-2060 while maximum temperatures increased at all sites (Figure 7). The projected resolution differed given the different source of climate-based variables used, 1 km^2 in the case of Zamora and Madrid and 5km^2 for Ourense and Valencia.

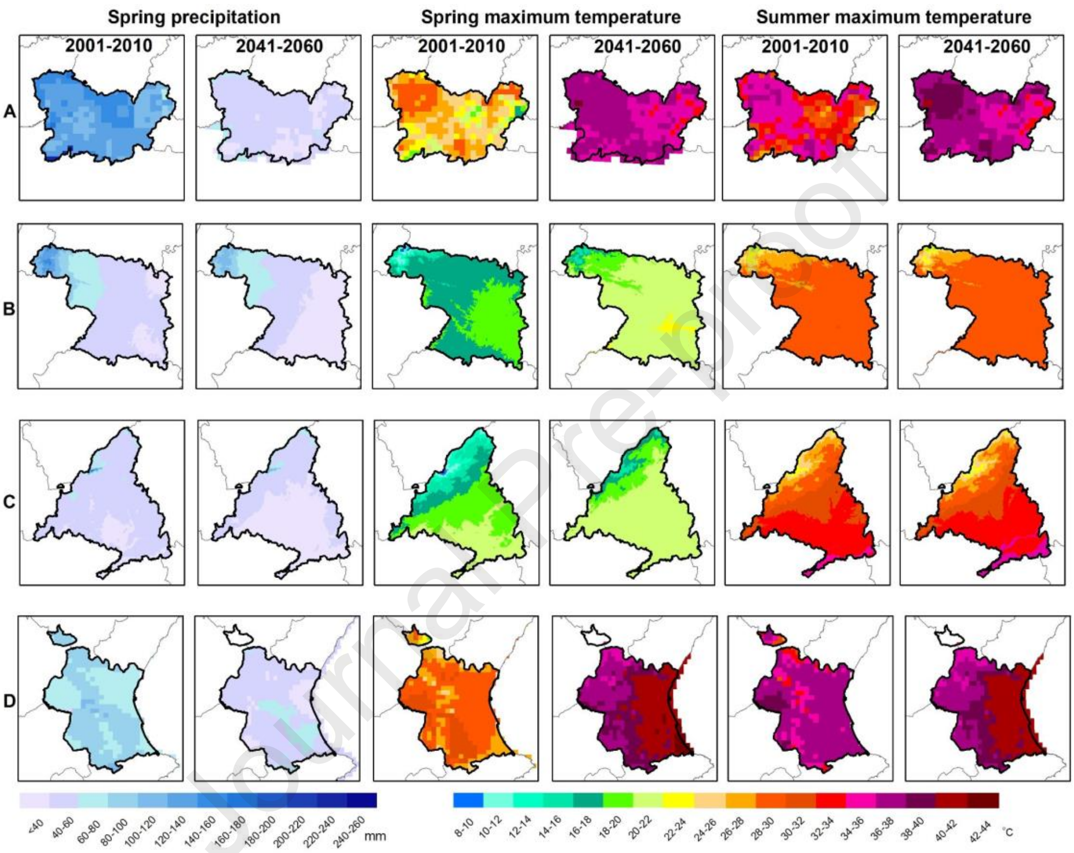

Figure 7. Average 2001-2010 and projected 2041-2060 spring precipitation (mm), spring/summer maximum temperature (ºC) in Ourense (A), Zamora (B), Madrid (C) and Valencia (D)

Concerning LFMC, the year 2005 was identified as the year more similar to projected year 2050 (center of the 20-year period from 2041 to 2060) climate conditions in all sites and, thus, the LFMC for this year/epoch was considered input for the future wildfire prediction model (Figure 8). Seasonal differences can be noted within each site. In Ourense, summer values were higher than spring values due to the influence of higher LFMC in the months of June and July in the summer average and lower in March and April in the spring average (See Figure A.4). An agricultural patch located in the South of Ourense presented a diverse behavior by season depending on the year of the 2001-2010 time series, but dominating lower LFMC values in spring than in summer. Also some forested areas located in the North of Ourense presented lower LFMC values in spring than in summer.

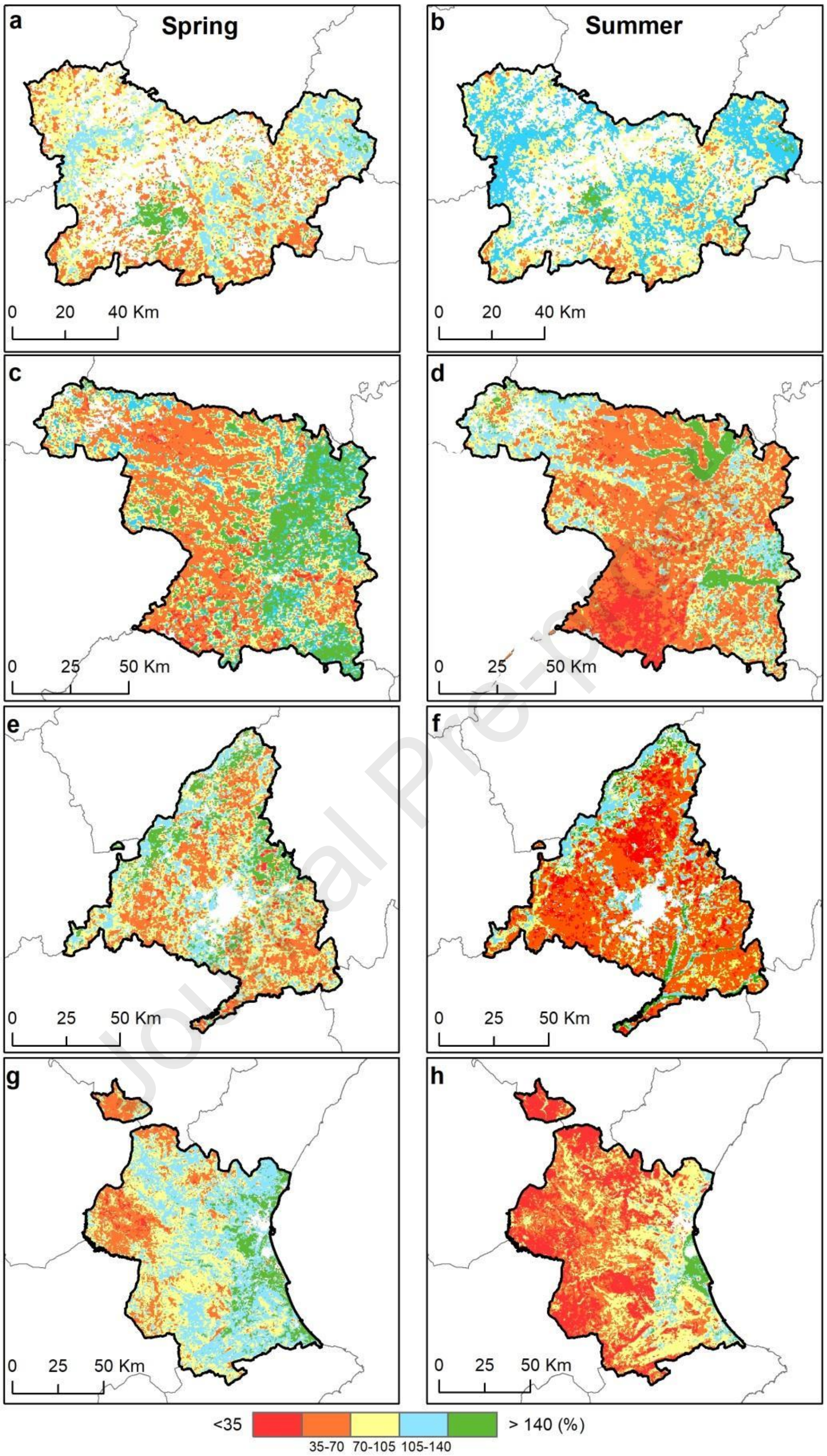

Figure 8. 2005 spring/summer LFMC in Ourense (a-b), Zamora (c-d), Madrid (e-f) and Valencia (g-h). Spring LFMC values were ~50-100% greater than summer values in Zamora (c), Madrid (e) and Valencia (g), and the spatial distribution varied between the seasons.

4.2.3. Projected wildfire occurrence

Projected wildfire occurrences for each year from 2041 to 2060 showed a similar pattern to the one estimated for the year 2050 which indicated the large contribution of the non-climate variables to the proposed model. The mean and the standard deviation of the 20-years period reflected a similar projected pattern and, regarding the level of uncertainty (given by the standard deviation), cells with high projected wildfire (0.9-1 probability values) retained at least intermediate values (~0.7). In addition, cells with intermediate projected wildfire were around the mean probability values (See Figure A.6).

Projected wildfire occurrence would increase in ~19-73% of the 1 km^2 grid cells, depending on the analyzed site, and decrease in ~26-80% (Table 7). In one site (Zamora) cells with an increase in projected wildfire occurrence were greater than the baseline model. In the other sites the percentage of cells that saw a decrease in projected wildfire occurrence outnumbered those that saw an increase.

Table 7. Percentage of 1 km^2 cells with an increase and decrease in 2041-2060 projected wildfire of occurrence

Study sites	Percentage of increase	Percentage of decrease
Ourense	19.1%	80.1%
Zamora	73.5%	26.4%
Madrid	32.1%	67.9%
Valencia	20.0%	79.9%

In Zamora (Figure 9b) and Madrid (Figure 9c) projected wildfire probability increases in two standard deviations were notable in the areas where the projected wildfire probability was expected to increase, while in Ourense and Valencia the increases were mostly within one standard deviation. In general, in Zamora and in Madrid, the probability of a wildfire occurring increased in 2041-2060 for areas where the baseline wildfire probability was higher (Figure 6). However, in Ourense and Valencia, this probability increased in areas where the wildfire probability baseline was intermediate or low. Moreover, in Ourense, projected wildfire probability decreases in some areas where the baseline probability foreseen intermediate values.

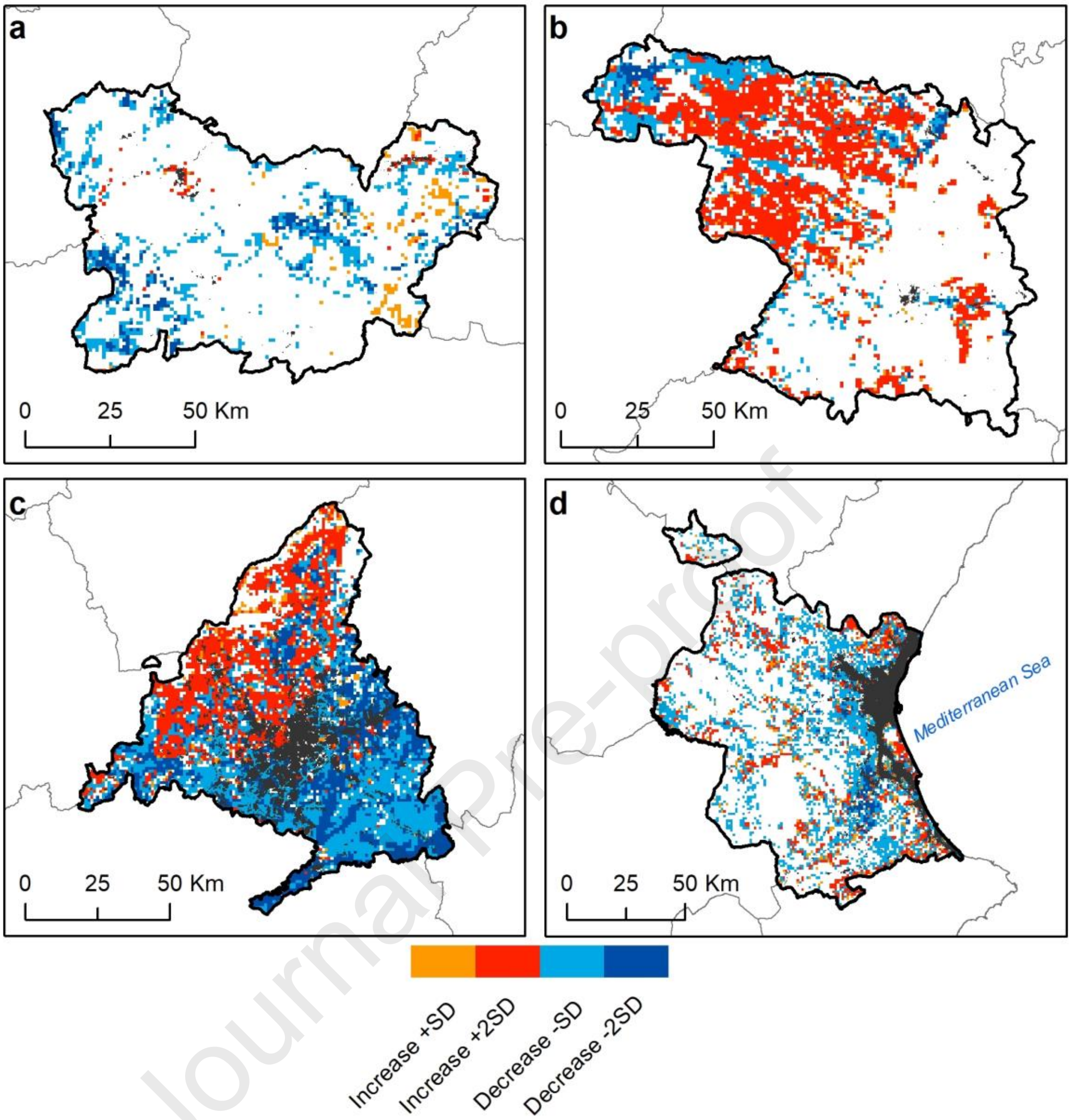

Figure 9. Increases and decreases in one (orange or light blue) or two (red or dark blue) standard deviation values from the average by 1 km^2 grid cells: Ourense (a), Zamora (b), Madrid (c) and Valencia (d). Black cells represent the projected 2050 urban areas and white color unchanged cells.

5. Discussion

This paper concludes that both LULC and climate changes will have an effect and drive future wildfire probability of occurrence. Drivers of change and resulting probability will vary across and within the analyzed sites. Projected wildfire probability will increase by target 1 km^2 grid cells mostly in Zamora site, where the percentage of cells with an increase will be larger than the percentage of cells with a decrease. Also, in this site and in Madrid higher projected values occurred where it was expected a higher increase. On one hand, the strength and characteristics of the relationships among LULC interfaces, aspect, climate and LFMC established in the baseline predictive models will determine future projected probability. On the other hand, the relative importance of drivers was different depending on the site but at the same time showed several key common points. For instance, wildfire occurrence probability increased because of LULC interfaces effect. However, their specific influence depended on the site. *WUI* presented a larger effect in the urban-developed sites (Madrid and Valencia), while *FAI* in the rural-oriented sites (Zamora and Ourense) as well as *FGI* in Ourense. This result is consistent with other studies done in Spain obtaining similar effects in distinguishing drivers that lead to wildfire occurrence in rural (*FAI* influence) and urban (*WUI* influence) areas (Martínez et al., 2009; Rodrigues et al., 2016). Consequently, our results entail considerations for management actions, e.g., ignition prevention efforts may be most effective if actions are concentrated on these specific LULC interfaces. Nonetheless, *WUI* was not significant in Ourense as found in previous research (Chas-Amil et al., 2013). CCI-LC LULC (300 m of spatial resolution) was used as the LULC data source. This data source was considered appropriate for modelling wildfire at the site al level (Vilar et al., 2019). However, in Orense the urban development structure is small and scattered (Balsa Barreiro and Hermosilla, 2013). According to Roy Chowdhury et al. (2018), for urban development studies CCI-LC does not detect the location of fringe areas as essential components of the urban settlement category. Because *WUI* is defined as the contact area between urban and forest covers, further work would be needed to categorize the urban category in these particular situations.

Factor effects on predicted probability were diverse by site. As expected for areas located in the Mediterranean Basin (Koutsias et al., 2013; Verdú et al., 2012), the maximum temperature increased the predicted probability in two sites (Madrid and Valencia). Moreover, spring precipitation in Ourense and Madrid and LFMC in Zamora decreased the probability of a wildfire, consistent with previous research in Mediterranean fire-prone areas. Less rainfall in spring has been analyzed as a contributor to increased wildfire occurrence in Valencia and Morocco (Chergui et al., 2018). Also, antecedent rainfall has been shown to have a relation with the threshold where LFMC declines and thus fires start in California (Dennison and Moritz, 2009). Therefore, more rain will delay the timing of this critical threshold and thus might be decreasing subsequent wildfires. However, the relationship between temperature and wildfire occurrence for the two rural sites (Ourense and Zamora) contradicted expectations: maximum temperature decreased wildfire occurrence. Nevertheless, the baseline model showed that the temperature effect was compensated by spring precipitation or LFMC, and factors determined by these variables decreased wildfire probability.

The resulting probability maps varied within the analyzed sites due to differences in relationships among drivers and response variable. In the case of the Madrid, mid-probability values were more abundant within its area and greater wildfire probability values were not spatial concentrated in the same cells as in previous papers (Vilar et al., 2016b). However, Vilar et al. (2016a), only included human-related factors as explanatory variables. Studies of historical fire prediction in Mediterranean areas using climate and land cover or human-related variables have shown differences in the strength that climate variables have in the control of estimated wildfire occurrence (Duane et al., 2015; Padilla and Vega-García, 2011; Verdú et al., 2012).

Future projected wildfire will depend on the obtained baseline current conditions and also on nature and the degree of change in climate and LULC. Among other concerns, LULC change scenario projection depends on the spatial and temporal characteristics of the data used for the simulation (Martínez-Vega et al., 2017). CCI-LC (available for every year since 1992) was chosen as the LULC data source as it was considered a standard source of information because of the global availability thereof, allowing studies to be replicated in other sites. Nonetheless, other studies in crop monitoring (Pérez-Hoyos et al., 2017), revealed this source led to the overestimation of the agriculture class, finding improvements in newer versions of the product (2015). This issue could have consequences in the amount of derived *FAI* that is calculated and estimated. The time points chosen for the analysis (1998 and 2008) happened after the more important land abandonment process that mainly occurred in the 1950s-1960s (Geri et al., 2010). Still, this change continued in the selected period and was reflected in the resulting general decline in agriculture, except for the Ourense site. Complementary explanatory variables could have improved the modelling of some of the LULC changes, such as future information on the road network for the projected centered year (2050). Acceptable overall accuracies were obtained in the validation of the BAU scenarios but there were misclassification results, mostly for the urban class. This can be explained by the fact that this category represented a small percentage of the total area of the sites, but a high percentage of change (mostly in the most developed, urban sites) (Gallardo et al., 2015). Also, even the good accuracy results found for the agriculture category in Ourense presented an error of commission of ~13%. This, in turn, increased this class, contrary to the expected general trend of land abandonment. Projected LULC was used as the data source for LULC interfaces calculation, so a detailed analysis of the accuracy in the location of the new LULC was desired. This could be improved by calculating quantity and allocation disagreements, which include exchange and shift components (Pontius Jr. and Santacruz, 2014).

In addition to LULC projected changes, future climate scenarios calculated provided data at 1 km^2 target resolution. The method applied to obtain the future climatology at 1 km (delta difference) of Bedia et al. (2013) assumes a constant bias, which is removed when the deltas are considered. This process has been satisfactorily applied in Madrid and Zamora sites, where historical climate data was able to be calculated at 1 km^2. Nonetheless, good results were also obtained by using SAFRAN data at 5 km^2 resolution. This method could be replicated for other sites if observed historical data are available as a reference. According to Moriondo et al. (2006)

the use of regional circulation models (RCMs) allows reproducing fine-scale features of different climates, making RCMs more reliable for climate change impact analysis and fire risk studies.

In general, future wildfire probability will increase at least in two sites (Zamora and Madrid), in areas where the expected baseline probability was high, consistent with projections made with the inclusion of the human factor in fire-prone areas (Gallardo et al., 2015; Liu et al., 2012; Syphard et al., 2018; Bryant and Westerling, 2014; Westerling et al., 2011). However, two other sites (Ourense and Valencia), showed fewer cells where the wildfire probability would increase. Also, projected wildfire probability decreased in cells where the expected baseline probability was intermediate or low. This was due to the less future *FGI* (Ourense), *FAI* and *WUI* (Valencia), thus reducing the probability of a wildfire. And also due to the effects, contrary as expected, of the reduction in the spring precipitation or an increase in the spring maximum temperature that will reduce the probability of a wildfire. Other papers also found that climate change was not always dominant in explaining future wildfire changes (Syphard et al., 2019).

The modelling framework applied in this paper for regional wildfire future predictions allowed for the establishment of a statistically-based wildfire occurrence baseline, which showed human-climate-LFMC driving relationships and strengths. Said baseline detected regional differences between studied zones in the estimated and the spatial distribution probability of wildfires. The dataset used referred to 1 km^2 target resolution based on detailed gridded spatial data, such as CCI-LC (300 m), climate (1-5 km) LFMC (500 m) and aspect (200 m). In future works, these methods can be extended and replicated in other study sites, as they have been separately widely applied and proven to provide accurate wildfire estimations in other areas. Also LULC CCI-LC and remote sensing data used to derive LFMC are available elsewhere. Nonetheless, some limitations can be found for a wider application. Well-observed climate data are needed to proceed to the downscaling process at 1 km^2. Also, combined climate and LFMC factors are not always easy to interpret and can cover the specific effect of each variable. Moreover, projected LFMC was approximated by analyzing climate current and future conditions, as no future field or remote sensing data were available for estimating LFMC. Further work is needed to find a way to forecast LFMC. Furthermore, even though the non-climatic variables largely contributed to the future wildfire occurrence, those were projected to a single year centered on the 20-year climate projections, which can limit the proposed modelling framework. LULC projections can be calculated for more than one target year if considering different past periods of change. This could contribute to enrich the projected wildfire occurrence within the 20-year climatic projected period, and future work will consider a multi-year LULC projections framework.

6. Conclusions

Future wildfire projections will result from the complex interactions among diverse factors related to human activities (LULC interfaces), climate and fuel moisture content (LFMC). Expected changes will produce an increase in wildfire occurrence in three out of four analyzed Spanish sites, indicating the existing variation in fire-climate and land-use effects by site. LULC change-projected scenarios properly simulated the conversion to natural vegetation and urban development, resulting in LULC interfaces that will have specific effects on projected wildfire by site. When taking management and planning actions, considering climate change conditions and the LFMC future worst-case scenario will also be important, as well as LULC change consequences and therefore the human factor. The modelling framework applied here can be replicated in other fire-prone sites, such as the LULC global CCI-LC product and remote sensing data used to derive LFMC are available elsewhere. Still, having detailed, observed climate data is necessary. This paper showed the results for a specific climate change regional model and one emission scenario, conditions that could be explored by using other available models. Also, LULC change predictions might be improved by applying different LULC scenario pathways (conservation, economic crisis) and considering multi-year projections. Future wildfire predictions in fire-prone and humanized areas at detailed spatial resolution and considering regional characteristics are useful for establishing mitigation measures for the future and can be useful to managers as a tool for planning actions to prevent wildfires.

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Highlights

- A modelling framework for estimating future wildfire occurrence in Land Use Land Cover and climate change scenarios is described
- LULC-derived interfaces and a combination of LFMC and seasonal climate-related variables were used as predictors
- Expected changes will mainly increase wildfire occurrence with varied effects by analyzed region
- Future wildfire predictions considering regional characteristics are useful for establishing mitigation measures and a tool for planning fire prevention actions

Declaration of interests

☒ The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

☐The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: