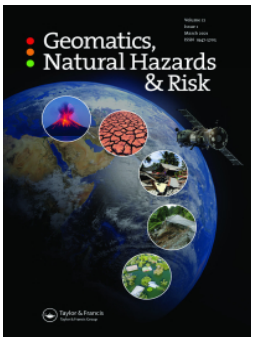

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Human-caused ignition pathways under climate change scenarios in Eastern Spain

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ABSTRACT

Wildfires pose an increasing threat to society, requiring appropriate approaches to understand the components of risk to design effective mitigation strategies. Under this premise, we present a comprehensive methodology to assess the probability of ignition of human-caused wildfires, one of the key drivers of risk. Our approach combines historical ignition records of fires larger than 5 ha (849 ignitions during 1998–2016) in eastern Spain and geospatial information regarding ignition variables. The method leverages the Random Forest algorithm to train a spatially-explicit model of ignition probability, combining distance to wildland interfaces and roads, population density, fuel types, and daily estimates of dead fuel moisture content (DFMC). The model was applied to outline the spatial pattern of probability under current conditions (2015–2020) and future projections across four Shared Socioeconomic Pathways (SSP1-2.6, 2-4.5, 3-7.0, and 5–8.5). The model achieved satisfactory predictive performance (AUC $= 0.76 \pm 0.01$). We observed a generalized increase in the probability of ignition in all scenarios linked to climate warming decreasing DFMC, except in SSP1-2.6. Furthermore, changes in population density fostered an increase in probability in rural and mountainous areas. Taken together, our findings make an important contribution to fire risk assessment and the development of adaptation strategies under different socioeconomic trends.

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Wildfire risk; GIS; modeling; ignition; SSP; climate projections

1. Introduction

Extreme wildfires pose a growing threat in Europe, exacerbated by climate change. In the summer of 2022, the continent experienced an unprecedented fire season linked to intense and prolonged heatwaves, with more than 660,000 hectares burned and particularly large fires in countries like Spain, Portugal, and France (European

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Commission Joint Research Centre 2023). The increase in the frequency and severity of wildfires is not an isolated event, but an alarming sign of changing climate patterns and human activities, which are reshaping fire regimes by coupling increasingly favorable weather conditions with expanding urban interfaces and fuel build-up (Pausas Juli and Fernández-Muñoz 2012; Moreira et al. 2020; Cochrane and Bowman 2021). Recent studies suggest a remarkable increase in the occurrence of extreme wildfire events and in the length of the fire season in Europe due to climate warming (Calheiros et al. 2021). Rising temperatures and reduced precipitation would enhance fire weather danger, further intensifying fire regime components such as ignition, burned area or fire size (Galizia et al. 2023). This looming situation accentuates the current challenges of wildfire science and policymaking. For example, risk mitigation would become more difficult and uncertain given the wide range of possible emerging scenarios (Chuvieco et al. 2023), while fire-prone regions are likely to expand, amplifying fire over southern Mediterranean regions (Galizia et al. 2023).

Under the premise of managing fire regimes and not fire (Cochrane and Bowman 2021), we provide a framework for understanding the implications on fire ignition of different scenarios towards the end of the twenty first century. We focus on anthropogenic ignitions, one of the key components of fire regimes and risk assessment (Chuvieco et al. 2014; 2023), especially in human-dominated fire regimes, such as Spain, where human-caused fires accounted for 97.6% of total fire occurrence and 94.2% of the burned area in the period 2000–2016 (MITECO 2022). We delved into the role played by human factors of ignition like human pressure on wildlands (e.g. urban expansion, recreational use of forests or arson), accessibility or presence of agricultural activities (Leone et al. 2009), along with fuels (Aragoneses and Chuvieco 2021) and fire-weather (Calheiros et al. 2021). Analyses were conducted in Eastern Spain, one of the most fire-affected regions in Europe (Koutsias et al. 2016), witnessing some of the largest wildfires in history that have occurred due to a wide variety of underlying factors (EFFIS 2018; European Commission Joint Research Centre 2023).

Our assessment is based on empirical models trained using machine learning algorithms from historical fire records (in the period 1998–2016) in combination with geospatial information on fire drivers (Bar Massada et al. 2013; Rodrigues and De la Riva 2014; Dorph et al. 2022; Ochoa et al. 2024). We processed information on land cover types, vegetation species, road network, and daily fire-weather data to create a set of spatial predictors like wildland interfaces, distance-based accessibility, or DFMC estimates using Geographic Information System (GIS) techniques. This approach is widely recognized in the literature on wildfire risk assessment (Leone et al. 2003; Chuvieco et al. 2010; 2014), with a number of studies devoted to fire ignition exemplifying it in different regions and spatial-temporal scales (Vega-Garcia et al. 1995; 1996; Vasconcelos et al. 2001; Romero-Calcerrada et al. 2008; Catry et al. 2009; Vilar et al. 2010; Padilla and Vega-García 2011; Oliveira et al. 2012; Martínez-Fernández et al. 2013; Oliveira et al. 2014; Rodrigues et al. 2014; Rodrigues and De la Riva 2014; González-Olabarria et al. 2015; Costafreda-Aumedes et al. 2017; Leuenberger et al. 2018; Rodrigues et al. 2018; Ochoa et al. 2024).

The range of modeling variables covers a variety of factors like human pressure on wildlands, accessibility to forest sites, use of fire as a tool, as well as certain environmental aspects that modulate ignition potential like fuel types and moisture content (Leone et al. 2009; Costafreda-Aumedes et al. 2017; Ochoa et al. 2024). The presence of urban settlements and activities (e.g. agriculture) near forestlands favor the occurrence of human-caused fires (Vacca et al. 2020; Bar-Massada et al. 2023). Accessibility is also a key factor in determining how often a source of ignition, such as those caused by engine sparks or discarded cigarette butts, can initiate a fire (Narayanaraj and Wimberly 2011; Zambon et al. 2019). Population density has been shown to be a reliable driver of fire ignition, especially in rural settings, serving as a proxy indicator for human presence and pressure on wildlands (Knorr et al. 2014; Jiménez-Ruano et al. 2023; Keeping et al. 2024). The probability of fire occurrence increases along with population density. However, in densely populated areas, this relationship stagnates and even decays (i.e. ignition likelihood decreases), as the proportion of wildlands declines towards impervious urban areas. Fuel types are also relevant in determining the chances of ignition. Grassland and shrubland communities favor ignition given the availability of fine fuels that are easy to desiccate (Aragoneses and Chuvieco 2021; Chicas and Østergaard Nielsen 2022). Climate and meteorological variables also play a leading role in predicting wildfire danger and risk (Finney et al. 2011; Chuvieco et al. 2023), being a typical component of ignition models (Badia et al. 2011; Costafreda-Aumedes et al. 2017; Ochoa et al. 2024). These factors are related to fuel aridity and dryness, providing a way to estimate fuel moisture content (Balaguer-Romano et al. 2022; Keeping et al. 2024).

The core and novelty of our proposal lies in the development of a robust model to predict the probability of human-caused ignition that incorporates dynamic factors in its estimates. Specifically, we seek to provide future projections of ignition likelihood based on the Shared Socioeconomic Pathways (SSP). Our hypothesis is that the probability of ignition will systematically increase due to climate warming and population increase, being these key drivers of ignition. To verify this assumption, we developed a spatial-explicit model to predict human-caused ignitions under Mediterranean conditions and apply it to investigate the potential variations over time under four SSP scenarios (SSP1-2.6, 2-4.5, 3-7.0, and 5-8.5). We (1) provide evidence of the performance of our model in predicting the probability of human-caused ignition, (2) demonstrate the linkages between population density, dead fuel moisture content and ignition, and (3) project future changes in the spatial patterns of ignition. In doing so, we yield valuable outcomes for risk assessment, by providing probabilistic estimates of ignition likelihood; risk mitigation, by identifying key factors that modulate ignition, thereby enabling proactive management; and policymaking, by illustrating the effect over time of different narratives of socioeconomic development, demographics and climate change.

2. Material and methods

2.1. Study area

The study area extends over the eastern Spanish Mediterranean region (Figure 1). The area encompasses the NUTS2 regions of *Región de Murcia* (ES620), *Comunidad Valenciana* (ES52), *Aragón* (ES24), and *Catalunya* (ES51), and the province of

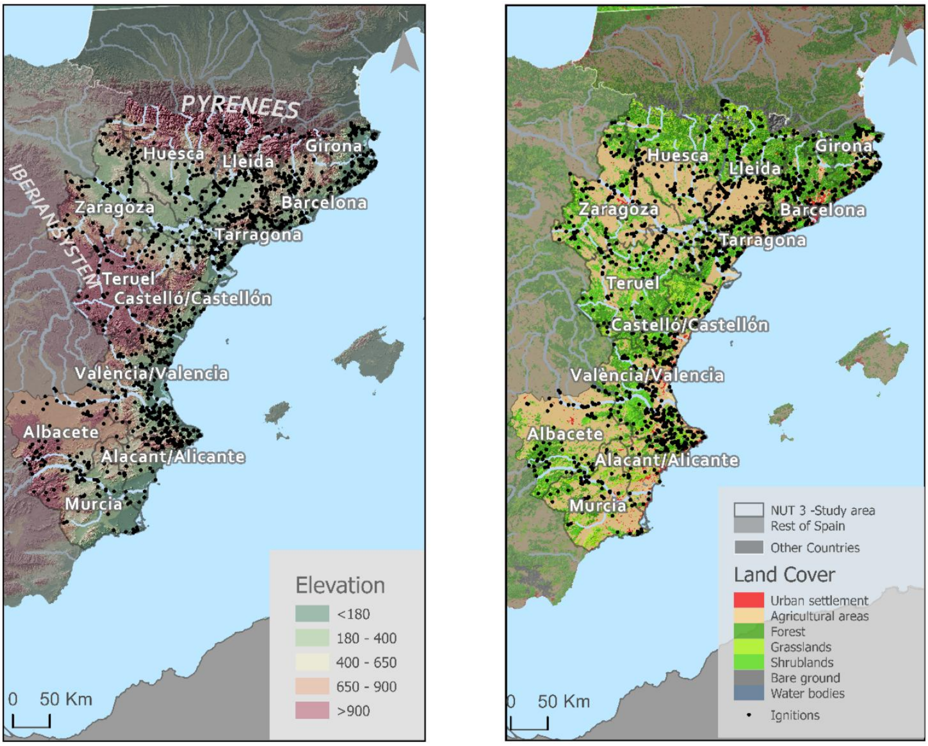

Figure 1. Location and main characteristics of the study area. Top panel shows the spatial distribution of elevation (m.a.s.l.); bottom panel dhows the distribution of land covers obtained from corine land cover.

Albacete (NUTS3, ES421). The area was defined to match the region of analysis of the project FIREPATHS, originally established according to the occurrence of very large (>15,000 ha burned) and severe wildfires during the summer of 1994 (Ministerio de Medio Ambiente 1995).

This region is characterized by a Mediterranean climate with a pronounced summer drought and high temperatures that significantly reduce fuel moisture content, with peak rainfall in spring and fall. Climate and meteorological conditions are milder and rainier along the coast, becoming more extreme and contrasting, with higher thermal amplitude, towards the hinterland. The region encompasses several mountain ranges that break this climate pattern, namely the south-eastern end of the *Sistema Ibérico* (up to 2,022 m.a.s.l.) towards the south of *Aragón*; the *Cordillera Costero-Catalana* (up to 1,712 m.a.s.l.), which runs parallel to the coast along *Catalunya*; or the Pyrenees (up to 3,404 m.a.s.l.) in the north of the study area along the border with France. These mountain ranges induce sharp thermal and rainfall gradients, at higher altitudes. The coastal range also plays a role in regulating air humidity inland, inducing a Foehn effect that reduces air moisture from easterly advections (Peña-Angulo et al. 2016). In between we find the *Ebro* River basin, a large low depression prone to windy conditions and thermal inversion during winter, with typical continental features (e.g. larger thermal range) accentuated by the sheltering effect of the surrounding mountain ranges (Martín-Vide and Olcina 2001). These contrasting conditions are known to affect the distribution of fire ignition and burned area.

The region exhibits a wide range of land uses and land cover types (European Environment Agency 2019a). Urban areas occupy the smallest fraction of land (2.5%), clustering along the coast, and in the center of Aragon. Agricultural land (43.5%) predominates in the western side of the study region, with irrigated crops along the main river corridors and rainfed crops in the interior. Vegetation land cover represents 52.2% of the region (8.4% grassland, 16.8% shrubland and 27.0% tree forest).

The dominant vegetation consists of Mediterranean-type communities, dominated mainly by *Pinus halepensis* and *Quercus ilex* as the major tree species, often with sclerophyllous shrubs in the understory. Serotinous pine species (like *Pinus pinaster*) dominate in the southern region of Aragon, while non-serotinous pines appear gradually as we enter the Pyrenees, with *Pinus nigra*, followed by *Pinus sylvestris* and *Pinus uncinate*—arranged along the altitudinal gradient—and spruce in the highest altitudes. Other tree species, such as *Quercus faginea* and *Fagus sylvatica*, intermingle in certain locations under suitable conditions. *Quercus suber* communities are also frequent in northeastern Catalonia. Maquis-like shrub formations are found in drier and warmer conditions, often growing on poor soils. Natural grasslands and pastures are located mainly on the alpine floor (>2300 m.a.s.l.), except for steppe communities of the Ebro Valley (Rivas Martínez 1987).

The study area shows distinctive patterns of population density and urban development (Padullés Cubino and Retana 2023). It contains 3 out of the top 5 largest metropolitan areas in Spain (Barcelona, Valencia and Zaragoza), all of them densely populated and in some cases close to forest areas (Bar-Massada et al. 2023). The region also encompasses areas with acute demographic problems, including depopulation and population overage due to rural exodus and agricultural land abandonment (Lasanta et al. 2017; Gelabert et al. 2022). This situation prevails outside metropolitan regions, in intensive agricultural-grazing areas (Zúñiga-Antón et al. 2022). From a wildfire perspective, depopulation leads to forest expansion, favoring fuel continuity and, consequently, fire spread (Alonso-Sarría et al. 2016), while densely populated areas and regions with a predominance of agricultural activities promote ignition.

2.2. Materials

2.2.1. Fire ignition data and response variable

The primary data source on ignitions was the EGIF database (as *Estadística General de Incendios Forestales* in Spanish), published and maintained by the Spanish Ministry for Ecological Transition and Demographic Challenge (MITECO 2022). This database collects valuable information from official fire extinction reports, including data on the location of the ignition point, the ignition source, deployed suppression means, the burned size of the burned area, and affected vegetation covers, among others (Mérida et al. 2007). It is one of the oldest and most comprehensive database in Europe, compiling fire records from 1968 until 2016.[1] The quality and accuracy of the information has gradually increased over time, reaching reliable accuracy in the location of the ignition point (GPS-located) and fully compiling all fires (larger than

1 ha burned) during the 90s (Vélez 2001). Accordingly, we set the temporal span of analysis to the period 1998–2016.

Using the EGIF database we built our response variable to model the probability of ignition due to anthropogenic causes. We derived a binary variable that consists of 1/0 Boolean values, where 1 signifies the occurrence of an ignition event and 0 indicates its pseudo-absence. Ignitions (coded as 1) were defined as all fire records with a burned area exceeding 5 hectares (Syphard et al. 2011; Chuvieco et al. 2014; Rodrigues et al. 2014) and attributed to anthropogenic causes, including accidental, negligent, or deliberate (arson) ignition sources. Pseudo-absence[2] of fire (coded as 0), were generated for areas with no recorded ignition events. The application of a size threshold (>5 hectares) was intended to focus the analysis on fires with significant ecological and social consequences. This threshold aligns the model with real-world management priorities by emphasizing larger, more impactful fires (Syphard et al. 2007; Finney et al. 2009; Moreno et al. 2011).

A total of 849 fire ignition events were identified using the coordinate pairs provided in the database. These ignitions accounted for 98% of the burned area during the study period while representing 59% of all recorded fire events (EGIF; MITECO 2022). Pseudo-absence points were positioned by constructing random point samples with the same number of observations as the ignition sample (849 pseudo-absence points) as recommended for modeling highly imbalanced datasets (Fernández et al. 2018). Pseudo-absence points were constrained to regions where ignition events did not occur during the study period but holding the potential to support a fire (i.e. vegetated areas according to Corine Land Cover in 2012; European Environment Agency 2019b). Otherwise, non-fire locations might fall in regions unable to support ignition (e.g. barrens or water layers), artificially inflating the model's predictive performance. To mitigate potential bias or uncertainty from the random placement of pseudo-absence points, we generated 100 independent samples. We subsequently assessed the potential variability in model outcomes arising from these alternative samples to ensure the robustness of our findings.

2.2.2. Explanatory variables

The explanatory variables were selected based on the existing literature on modeling ignition likelihood due to human causes (Costafreda-Aumedes et al. 2017; Chicas and Østergaard Nielsen 2022). The selected variables represent critical anthropogenic, environmental, and climatic drivers of ignition likelihood, enabling a comprehensive analysis of human-caused wildfire events.

Urban and agricultural land uses are often found adjacent to forested areas, creating boundaries or interfaces that can promote ignition. Therefore, the distance to the Wildland-Urban Interface (WUI) and the distance to Wildland-Agricultural Interface (WAI) were included as key variables. These were calculated as the Euclidean distance to the boundary lines between urban/forest and agricultural/forest polygons, respectively, using data from the Corine Land Cover 2018 (100 m) dataset (European Environment Agency 2019a). In addition to land-use interfaces, the distance to the road network was also considered, as roads are often associated with increased human presence and activity, which can lead to fire ignitions. This variable was derived as the Euclidean distance to roads, based on vector layers from the BTN25 v1 2018 (*Base Topográfica Nacional* 1:25000), a digital vector version of the Spanish topographic maps (IGN 2018) representing the year 2016. We also considered the population density, one of the most widely used variables to characterize the spatial distribution of population in modeling human-caused ignitions. We retrieved the dataset of population density (at 1 km resolution) from the Socioeconomic Data and Applications Center, concretely the year 2010 of the Gridded Population of the World, Version 4 (Gao and Pesaresi 2021b). To incorporate the effect of fuel types, we used the product developed by Aragoneses and Chuvieco (2021), which outlines the distribution of Rothermel's fuel types across Europe at 300 m of spatial resolution for the year 2020. Fuel types were introduced in the models as a categorical variable. Finally, from a climatic perspective, dead fine fuel moisture content (DFMC), was used to capture temporal variations in fuel flammability In accordance with the methodology of Rodrigues et al. (2024), we estimated daily DFMC from vapor pressure deficit (VPD), which we derived using ERA5 Land Reanalysis (9 km) temperature and relative humidity data (Copernicus Climate Change Service 2019); which were later linked to fire records based on the ignition date.

We hypothesized that the probability of ignition would increase near the wildland-urban and wildland-agricultural interfaces, as well as the road network, given their association with human activities. Similarly, higher population densities were expected to correlate with an elevated probability of ignition, particularly in small to medium urban areas where human presence and activity are more pronounced. From a climatic perspective, lower DFMC values were anticipated to enhance ignition likelihood, especially in areas dominated by shrubland-type fuel layers, where fine fuels are more susceptible to combustion under dry conditions.

Distance-based variables (distance to WUI, WAI, and roads) were calculated at 250×250 meters. Population density was extracted at 1×1 km, DFMC at 9×9 km, and fuel types at 300×300 m). All variables were upscaled to the coarsest resolution (9×9 km) using nearest neighbour interpolation, and extracted at both ignition points and pseudo-absence fire locations

2.3. Methodology

2.3.1. Model calibration and testing

We used the Random Forest algorithm (Breiman 2001) to train a binary classification model aimed at estimating the probability that a given observation belongs to the category '1-Presence' or occurrence of a fire. The algorithm requires the tuning of several hyperparameters, namely the number of predictors used at each split (*mtry*), the total number of trees in the forest (*ntrees*), and the minimum number of observations in the terminal nodes (*min node size*). These hyperparameters were optimized during the calibration phase using 10-fold cross-validation with 5 repetitions to ensure robust model performance.

We assessed the performance of the models by calculating the area under the receiver operating characteristic curve (AUC), which is a common metric for evaluating classification models. AUC is a threshold-independent measure of accuracy, plotting the true positive rate (sensitivity) against the false positive rate (1—specificity) along the range of probability thresholds (0–1). Furthermore, we calculated the Moran's I coefficient to assess the spatial independence of the residuals, ensuring there was no spatial autocorrelation. We also determined variable importance using the Gini impurity measure, expressing the overall contribution of each variable to the model as a percentage (0–100). All processes were carried out in the R environment (R Core Team 2023) using the *caret* package (Kuhn 2008) for model training, *sf* (Pebesma 2018) for spatial data handling, *terra* (Hijmans 2020) for raster data analysis, and *ape* (Paradis and Schliep 2019) for statistical analysis.

We calibrated 100 models (one for each pseudo-absence sample) building different replicates by bootstrapping the initial set of observations. This technique involves generating multiple random samples of data and training a model on each sample. For each model realization, we evaluated model performance and spatial autocorrelation in the residuals. Likewise, we retain information about feature importance. This enables us to provide a measure of uncertainty in model outputs. The final candidate model was selected based on the AUC closest to the median across the 100 AUC values among all models. This approach ensured that the final model was not biased by any individual sample and accurately reflected consistent performance across multiple iterations.

2.3.2. Spatial-temporal projections

Our model allows us to construct probabilistic predictions for different temporal horizons under different scenarios. After selecting the final model, we made predictions of human-caused ignition probability for both the current period (2015–2020, coincident with the overlap period for bias correction of the climate datasets) and future projections (by 2100; Jones et al. 2020), illustrating the pattern and evolution of ignition likelihood across the study region. To do so, we considered four representatives SSP from Coupled Model Intercomparison Project Phase-6 (CIMP6). SSP provide a framework to examine how societal factors such as demographics, economics, and technological development may evolve over time. They provide contrasting narratives depicting alternative socioeconomic trends leading to different emission outputs and, hence, warming scenarios (Riahi et al. 2017). The SSPs have been used to develop climate projection experiments (C3S, 2021) and to extrapolate population trends (Gao and Pesaresi 2021a), two of the key components of our modeling approach. Therefore, the variables that were considered to vary over time under the SSP scenarios included DFMC and population density.

Currently, CMIP6 experiments are considered the most suitable climate projections to assess the impacts of climate change. We evaluated four SSP scenarios: SSP1-2.6, a 'green' scenario focused on limiting global temperature increase to 1.5 °C by 2100 with climate protection measures promoting sustainable development; SSP2-4.5, a moderate emissions pathway with climate mitigation efforts, resulting in an average temperature increase of 2 °C–2.5 °C; SSP3-7.0, an intermediate scenario between SSP2 and SSP5, where some regions face environmental damage and temperature is expected to rise by 3 °C–4 °C; and SSP5-8.5, which represents a high emissions scenario with intensive fossil fuel use, leading to a temperature increase of up to 5 °C.

Future projections of DFMC were based on CMIP6 Earth System Models (ESMs), with a downscaling procedure applied to retrieve the necessary variables for its calculation, such as air temperature and relative humidity (Rodrigues et al. 2024). Specifically, the models ACCESS-CM2, CanESM5, CNRM-ESM2-1, EC-EARTH3, MPI-ESM1-2-HR, and MRI-ESM2-0 were used under the four SSP scenarios, with bias correction applied using historical experiments from the 2015–2020 period. These models provided daily temporal resolution, and their outputs were downscaled to a spatial resolution of 9×9 km. Climate projections were obtained using a two-step downscaling approach based on parametric quantile-quantile mapping (Benestad 2010; Monjo et al. 2014), with ERA5-Land (approximately 9 km spatial resolution) serving as the reference dataset. For each specific ESM output, climate variables were downscaled to the reference grid points of the ERA5-Land by comparing the Empirical Cumulative Distribution Function (ECDF) of the reanalysis with the ECDF of the historical experiment of the climate model, previously bilinearly interpolated. To reduce computational cost, we selected polynomial curves for the quantile-quantile mapping functions, instead of the exponential distributions used by Monjo et al. (2014, 2016). Finally, parametric functions were applied to correct the SSP projections on a daily scale. DFMC was calculated using the multi-model model mean of temperature and relative humidity.

Population density projections under SSP scenarios were obtained from the 'Global 1-km Downscaled Population Base Year and Projection Grids Based on the Shared Socioeconomic Pathways, Revision 01' (Gao and Pesaresi 2021a, 2021b), provided by the Socioeconomic Data and Applications Center (SEDAC). The dataset includes global urban, rural, and total population data for the base year 2000, as well as population projections at ten-year intervals from 2010 to 2100, at a resolution of 1 km (approximately 30 arc-seconds).

DFMC projections were aggregated (calculating the 5th percentile) at ten-year intervals to match population density. Finally, all variables and spatial projections were upscaled to the coarsest resolution (9×9 km) for generating spatial predictions and mapping.

3. Results

3.1. Performance of the model and drivers of ignition

All models attained a satisfactory performance in predicting human-caused ignition probability (Figure 2A), with variability across the 100 realizations ranging narrowly from 0.78 to 0.84. In addition, the residuals showed no spatial autocorrelation for all models (Moran's I p-value > 0.05), ensuring the spatial independence of model error. The analysis of feature importance (Figure 2B) revealed the prominent role of DFMC in predicting human-caused ignitions, exhibiting a relative importance consistently exceeding 90%. DFMC was closely followed by the WAI, alongside distance to roads and the WUI. These three factors contributed similarly to distinguishing historical ignitions, with approximately 80% importance. Population density followed, yielding an average importance of 75%. The least contributing factor was the fuel type.

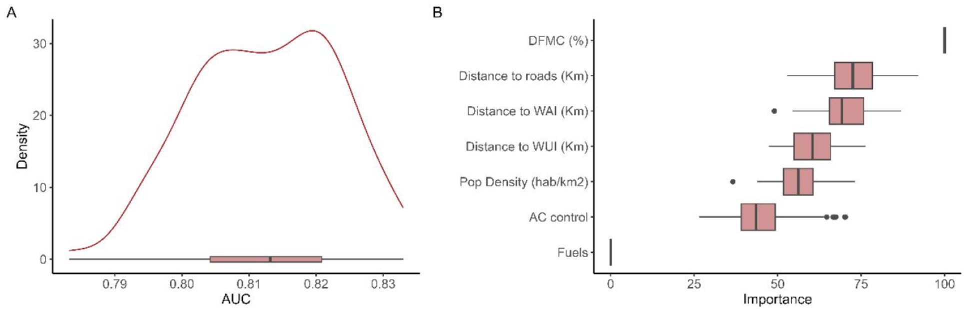

Figure 2. (A) Density plot of AUC values obtained from the 100 models calibrated. The solid line shows the density distribution while the horizontal boxplot displays the position of the median AUC (final model with AUC = 0.769), the first and third quartiles, and the minimum and maximum AUCs. (B) Boxplot diagram of feature importance. Horizontal boxplots display variability in relative importance from the 100 model realizations.

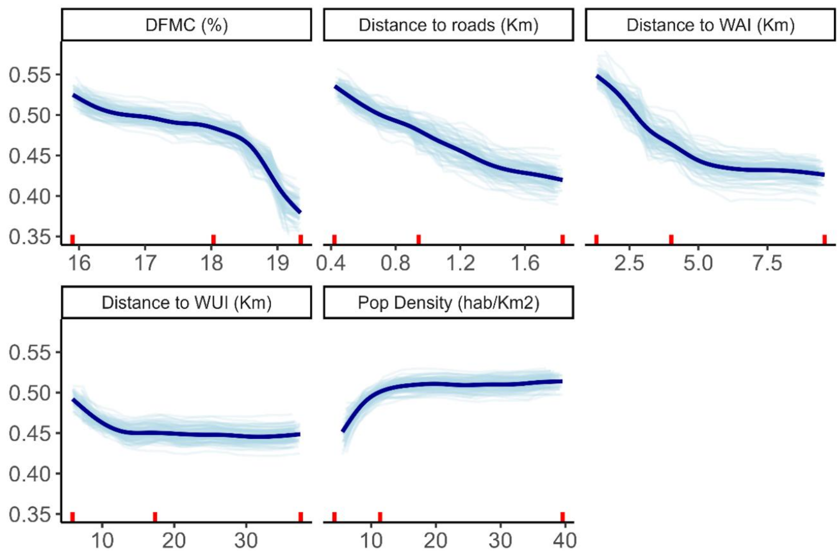

Figure 3. Partial dependence plots of the relationship profiles between model covariates and the predicted probability of human-caused ignition. Dark blue lines display the average relationship while light blue lines indicate the profiles of each individual model ($n = 100$).

Partial dependence plots (Figure 3) supported these findings by illustrating the relationship between predictors and ignition probability. The largest variation in ignition probability was observed in DFMC, with a range of 0.4 on the probability scale. Next, we found the WAI and the distance to roads, with approximately 0.2 change in probability, followed by population density and the distance to the WUI with a marginal variation of 0.15. Fuel types (Figure 4) were again the least important driver, with an average marginal change in contribution around 0.02, from 0.50 in ‘Short grass’ down to 0.48 in the ‘Logging slash’ model.

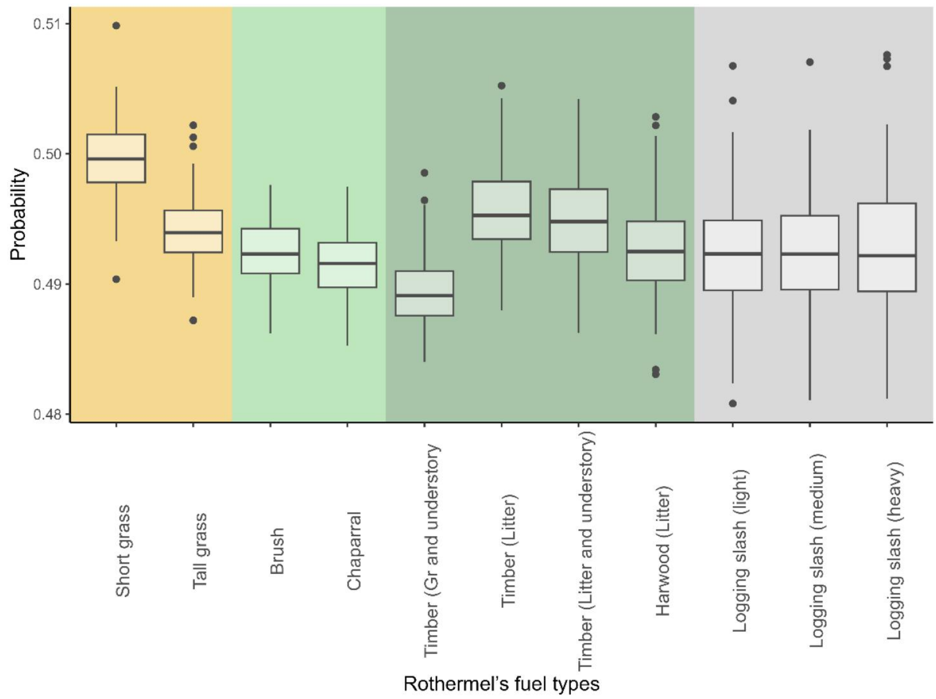

Figure 4. Change in ignition probability according to fuel types categories corresponding to the rothermel's fuel types (Rothermel 1972).

3.2. Spatial-temporal trends in ignition probability under SSP

The spatial distribution of ignition probability (Figure 5, left) under current conditions (2015–2020) revealed marked spatial variations across the study region. Higher probabilities were observed along the coast, particularly clustering around the main metropolitan regions of Barcelona and Valencia. In turn, the road network connecting the coast in Catalonia and the eastern Pyrenees fostered higher probability values up to the mountain range. Intermediate probability areas extended inland along the road corridor connecting Barcelona and Zaragoza, running parallel to the Ebro River. These areas also extended toward the inland regions of Murcia and Albacete. The western part of the Pyrenees, located in Aragon, reached the lowest probability of ignition, along with the province of Teruel, with a sharp change in probability compared to its neighboring regions.

Projected ignition probabilities under SSP scenarios revealed contrasting trends towards the end of the century (Figure 6). The trajectories under all scenarios remain nearly parallel until 2050, after which differences in socioeconomic trends trigger significant changes leading up to 2100. Scenarios projecting warming beyond 2 °C (SSP2-4.5, 3-7.0, and 5-8.5) anticipate a generalized increase in ignition probability. In SSP5-8.5, this increase is further exacerbated by denser population patterns. This increase closely mirrors the decline in DFMC (Figure 5 top-tight). Consequently, SSP2-4.5 is projected to increase by a margin of 0.04 until 2070, stagnating thereafter. Under SSP3-7.0, the increase would continue until 2100, reaching an average of plus

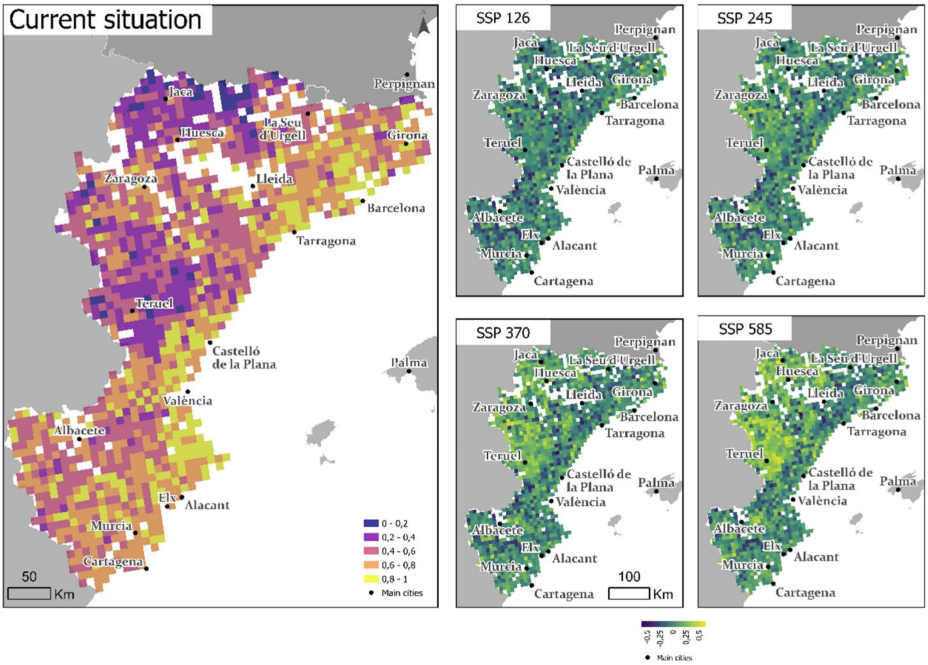

Figure 5. Spatial pattern of ignition probability under current conditions (2015–2020) and raw change in predicted probability for each SSP scenario by the year 2100. Source: elaborated by the authors; basemap credits: Instituto geográfico Nacional.

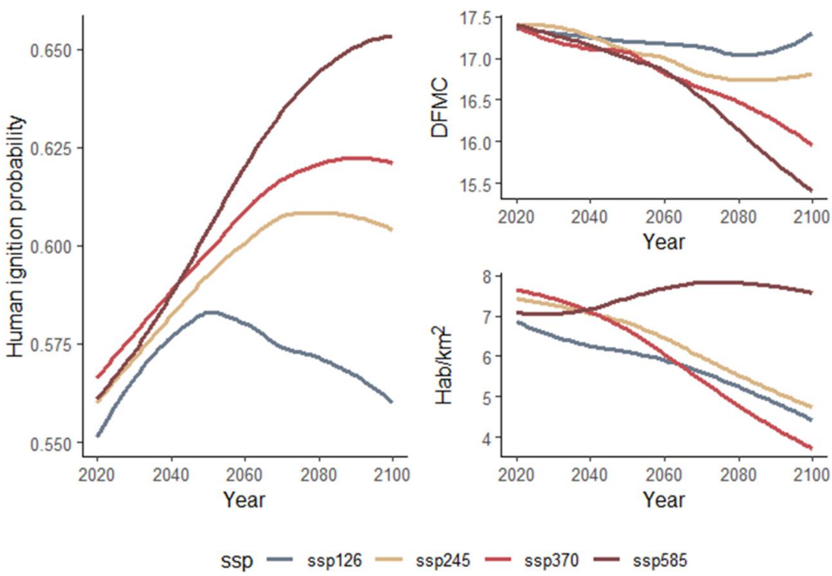

Figure 6. Left, change in average ignition probability in the study area under SSP scenarios. Each curve shows the average predicted probability of ignition from the ensemble estimate. Top-right, decadal means estimated change of DFCM using the CMIP6 models ACCESS-CM2, CanESM5, CNRM-ESM2-1, EC-EARTH3, MPI-ESM1-2-HR, MRI-ESM2-0. Bottom-right, the decadal average projection SEDAC population density under SSP 126, 245, 370, and 585.

0.07 by 2100, but at a slower rate compared to SSP5-8.5, which represents the worst-case scenario (plus 0.10 average increase). In contrast, in SSP1-2.6 the trend exhibits a piece-wise profile, increasing until 2050 and then decreasing below the current threshold by 2100.

However, the spatial distribution of these changes is uneven (Figure 5, right panels). In SSP2-4.5, SSP3-7.0, and SSP5-8.5, significant increases in ignition probability are projected within the Autonomous Region of Aragón, particularly in areas currently characterized by low ignition probabilities. This shift results from rising population densities and reduced DFMC due to warming. Conversely, under SSP1-2.6, some regions are expected to experience a slight decrease in ignition likelihood, particularly in areas where sustainable development mitigates climatic and demographic pressures.

4. Discussion and conclusions

4.1. The drivers of ignition

The historical occurrence of ignition is predominantly explained by the selected variables (AUC = 0.81; Figure 2), as indicated by their importance and marginal effects on ignition probability (Figures 2 and 3). DFMC emerged as the most critical driver, outperforming all other explanatory factors. Fuel moisture content is inversely related to probability of ignition, as it modulates the energy required to start a fire. A significant portion of this energy must first be invested to evaporate the moisture within fuels, meaning higher water content necessitates greater energy, while low moisture content facilitates ignition (Dimitrakopoulos 2001). DFMC, and related weather factors, such as temperature, relative humidity and VPD, have been used in prior modeling attempts in Spain (Chuvieco et al. 2010; Martín et al. 2019) and other Mediterranean-type regions (Bowman et al. 2019; Clarke et al. 2019). These factors are significant in influencing the dryness of the fine fraction of dead fuels (Camiá et al. 2009; Bedia et al. 2013; Resco de Dios et al. 2015).

Proximity to roads was identified as a relevant factor in initiating fires, with a sharp reduction in ignition probability as distance increases (Zambon et al. 2019), consistent with findings across Europe (Jiménez-Ruano et al. 2023; Ochoa et al. 2024). Next, in importance was the proximity to the WAI, one of the main drivers of ignition in the Spain (Leone et al. 2003; Chuvieco et al. 2014; Rodrigues et al. 2014). Agricultural burnings are one of the primary causes of ignition in Spain, often stemming from accidents or negligence during activities such as clearing harvest residues, pruning, or maintaining crop plots (Camia et al. 2013; MAPAMA 2019). The WUI, along with population density, also contributed meaningfully to ignition probability, reflecting increased human activity in wildland areas (Leone et al. 2003). Fires in Mediterranean regions frequently start in the vicinity of the WUI (Ganteaume et al. 2021) or in rural areas with high population density (Keeping et al. 2024; Ochoa et al. 2024). The WUI configuration, closely linked to mid-tier densely populated areas, is of critical importance for wildfire management (Ganteaume et al. 2021; Bar-Massada et al. 2023), given its diverse spatial arrangements (e.g. intermix areas or interface boundaries).

4.2. Dynamics under SSP scenarios

Wildfires are globally becoming more extreme and intense, a trend predominantly driven by diminishing fuel moisture content. This decline is linked to the intensification of fire-weather driven by atmospheric humidity and temperature (Jain et al. 2022). In alignment with this understanding, our model denotes a substantial influence of DFMC in determining the probability of ignition (Figure 2A).

Global change projections consistently indicate a notable augment in the occurrence of extreme fires and the expansion of fire-prone regions (Tedim et al. 2018; Calheiros et al. 2021; Galizia et al. 2023). In the Mediterranean basin, heat-driven fires are expected to become more likely towards the end of the twenty first century due to warmer conditions. Ruffault et al. (2020) project an increase in heat-induced fires in Spain under RCP4.5 (comparable to SSP2-4.5) and RCP8.5 (which resembles SSP5-8.5). According to their results, fires linked to drought events are projected to increase in frequency by 10%–20% in northeast Spain under RCP4.5 and by 20-30% under RCP8.5. In turn, heat waves would trigger a similar change in fire frequency but notably stronger under RCP4.5. The effect induced by climate change according to our projections of DFMC matches that pattern (Figure 5). In turn, the eastern end of Spain is expected to intensify in terms of fire incidence, experiencing more frequent and larger fires linked to gradually more hazardous fire weather conditions (Galizia et al. 2023). By incorporating detailed projections of future population distribution, our results provide a nuanced perspective on ignition likelihood, complementing and corroborating these broader findings.

Our predictions highlight notable differences in ignition likelihood based on future socioeconomic trends. These differences are shaped by the interplay between population density, which modulates human pressure, and climatic changes, which influence DFMC. Population density emerges as a key driver, with its effects especially pronounced in rural areas (Keeping et al. 2024). In Spain, rural regions have been shaped by a long-standing migration towards urban centers, a trend that continues to have profound implications for wildfire dynamics. The most evident consequence of this urban migration is land abandonment, particularly in mountainous regions with lower agricultural productivity (Lasanta et al. 2017). The decline in agricultural activity has disrupted traditional Mediterranean landscapes, increasing fuel availability and continuity. Depopulation and over aging is another side effect, further exacerbating these issues, with clear implications for ignition likelihood. Consistent with previous studies, our results suggest larger probabilities under increasingly densely populated patterns up to a threshold (Figure 3). This relationship profile translates into low probabilities under current conditions in low-density population areas of Aragon such as *Teruel* or the western Pyrenees. However, the SSP5-8.5 scenario projects a potential return or growth of population to these regions, which could elevate ignition probability in historically less vulnerable areas. In parallel, the increase in population density is expected to be accompanied by the expansion of the WUI, both in low and highly populated regions. WUI fires play a crucial role, not only due to the increased ignition probability (Figure 3) but also because of higher exposure to fire (Rodrigues et al. 2014; Vacca et al. 2020; Ganteaume et al. 2021). These findings underscore the urgent need for tailored management prescriptions to foster risk mitigation and resilient societies.

4.3. Implications for wildfire risk assessment and mitigation

The probability of ignition is a key component of risk assessment, as emphasized in recent European frameworks (CEU. JRC 2022; Chuvieco et al. 2023). The predominance of anthropogenic factors in fire ignition (Dijkstra et al. 2022) stresses the need for robust approaches. We advocate for incorporating dynamic calibration factors to enable ignition predictions across multiple temporal scales (Martín et al. 2019; Rodrigues et al. 2023), bridging the gap between operational short-term forecasting, historical trends, and long-term projections, enhancing the capacity to assess risks comprehensively. When combined with existing probabilistic models of natural ignition and fire containment capacity, our methodology offers deeper insights into extreme fire occurrence probabilities, allowing for more targeted management recommendations.

We revealed contrasting patterns of ignition under current and future conditions that deserve specific management prescriptions. In sparsely populated areas, where ignition probability is projected to rise, high fuel availability demands specific interventions. For example, encouraging fuel reduction and landscape mosaics through the recovery and maintenance of abandoned plots, or promoting traditional livestock activities such as grazing, could help mitigate fire risk. These measures would help control potential fire activity, revitalize rural settlements, and confront depopulation (Lasanta et al. 2015; Lloret et al. 2024).

The WUI represents another critical focus area, as it is a prevalent land cover system across Europe. The WUI covers approximately 7.4% of land in Europe, with the Mediterranean coast among the main hotspots of WUI concentration (Bar-Massada et al. 2023). Effective WUI risk management requires a thorough understanding of its configurations and the underlying drivers of risk. Push factors, such as urban sprawl, often lead to WUI expansion near consolidated urban areas, increasing human pressure on wildlands and, consequently, the occurrence of fires (González-Olabarria et al. 2015; Alcasena et al. 2017). In such situations, ignition prevention and public risk awareness campaigns are essential. Conversely, pull effects driven by the appeal of living near natural and recreational amenities, drive WUI growth closer to wildlands, creating intermixed landscapes of forest and human settlements. These dynamics are particularly pronounced in areas experiencing re-population of previously abandoned lands (Badia et al. 2019).

Addressing these challenges requires detailed spatial and temporal data on risk factors to inform management strategies (Moritz et al. 2022), such as those featured in this study. Such knowledge is vital for designing streamlined interventions that reduce fire risk while fostering resilience in both rural and urban communities.

Notes

1. Note that at the date this manuscript is being written fire data from the EGIF database is only available until 2016.

2. The term pseudo-absence applies when data on true absences is not available. It involves generating artificial absence points to contrast with presence data (where wildfires have been observed) to build predictive models (Bar Massada et al. 2013).

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Authors' contributions

Gelabert Vadillo, Pere Joan: Methodology, Data curation, Investigation, Formal analysis, Visualization, Writing- Original draft preparation, Validation; Jiménez-Ruano, Adrián: Methodology, Data curation, Editing; Ribalaygua, Jaime: Data curation, Editing; Torres Luís: Data curation, Editing; Rodrigues, Marcos: Conceptualization, Methodology, Investigation, Formal analysis, Supervision, Writing- Original draft preparation, Funding acquisition.

Disclosure statement

The authors declare no conflict of interest.

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Data availability statement

Fire data and original GIS layers are freely available at the following repositories and websites: EGIF (https://www.miteco.gob.es/es/biodiversidad/temas/incendios-forestales/estadisticas-datos.html), CNIG (http://centrodedescargas.cnig.es/CentroDescargas/catalogo.do?Serie=MAUT), EEA (https://land.copernicus.eu/en/products/corine-land-cover), and SEDAC (https://sedac.ciesin.columbia.edu/). All probability maps and spatial datasets produced in this study are freely available from the corresponding author on request. Climate projections belong to Meteogrid S.L. and its availability is subject to formal request.

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