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Next-gen regional fire risk mapping: Integrating hyperspectral imagery and National Forest Inventory data to identify hot-spot wildland-urban interfaces

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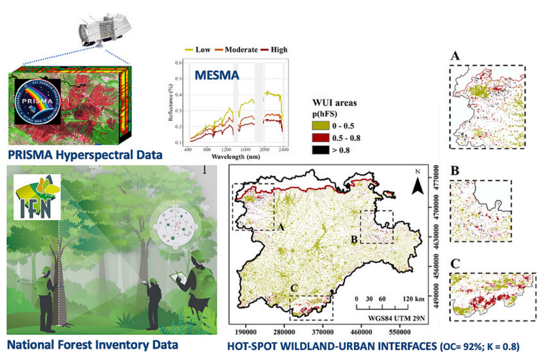
HIGHLIGHTS

- Forest management needs accurate hot-spot WUI maps showing high severity fire risk.
- We introduced a next-generation fire risk assessment method focused on WUI zones.
- Fire severity was estimated by Multiple Endmember Spectral Mixture Analysis (MESMA).
- Generalization at regional scale of fire severity map using NFI data
- Method applied in a Mediterranean ecosystem, but with potential for extrapolation

GRAPHICAL ABSTRACT



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ABSTRACT

The increasing threat of high-severity wildfires in Mediterranean Wildland-Urban Interface (WUI) areas demands to develop effective fire risk assessment and management strategies. Simultaneously, the newfound accessibility of spaceborne hyperspectral data represents a significant potential for generating fire severity assessments, whereas National Forest Inventories (NFI) offer a vast dataset related to vegetation and fuel loads, which is essential for shaping the planning and strategies of forest services. This research work aims to advance the state-of-the-art in WUI fire risk mapping in the western Mediterranean Basin by combining PRISMA spaceborne hyperspectral data and Spanish NFI data. The proposed methodology had three main stages: (i) fire severity assessment at local scale (a wildfire) by using PRISMA hyperspectral data and Multi-Endmember Spectral Mixture Analysis (MESMA) leveraging field-based measurements of the Composite Burn Index (70 plots); (ii) development of a high fire severity probability map at regional scale from the extrapolation of a Random Forest predictive model calibrated from fire severity estimates, NFI data and topo-climatic variables at local scale (overall accuracy = 92 %; Kappa = 0.8); and (iii) identification and characterization of zones that concentrate WUIs with high probability of high fire severity if a fire event occurs (hot-spot WUIs) by crossing the information

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from the previous regional high fire severity probability map and a WUI cartography developed at regional scale. Study area was Castilla y León Autonomous Region (larger Spanish region, 94,226 km^2), where the second-largest extreme Spanish wildfire event (28,000 ha) occurred. We identified hot-spot WUIs so that stakeholders and decision-makers could (i) prioritize resources and interventions for effective fire management and mitigation, (ii) allocate resources for prevention, and (iii) plan evacuation measures to safeguard lives and property. This study contributes to the development of next-generation fire risk assessment methods that combine remote sensing technologies with comprehensive ground-level datasets.

1. Introduction

Wildfires are acknowledged as inherent disturbances in the Mediterranean Basin (Seidl et al., 2014; Koutsias et al., 2022; Pausas and Keeley, 2021) that have shaped historical renewal patterns and created mosaic-like landscapes (Fernandes, 2013; Jones and Tingley, 2022). However, the increasing frequency of hot and dry summers, and the accumulation of fuel over time and space, are associated to the occurrence of extensive and intense fire seasons in this region (Barbero et al., 2015). For these reasons, severe wildfires are understood as disasters in many occasions not only because of their potential impacts on natural environment, but also on infrastructure and human lives (Fernández-García et al., 2022; Espinosa et al., 2023; Fernández-Guisuraga et al., 2023a) caused by urban growth into wilderness areas and/or abandoned agricultural lands (Fernández-García et al., 2023; Samara et al., 2018). Consequently, the Mediterranean Basin stands as an important fire-prone belt where the management of fire risk provokes significant attention. While fire risk management has conventionally centered around understanding the probability of fire ignition (Calviño-Cancela et al., 2017; Chen and Jin, 2022; Molina-Terren et al., 2019) and fire spread models (Hysa, 2021; Maffei et al., 2021; Massetti et al., 2019; Vacca et al., 2020), the concept of fire severity, understood as the extent of fire-induced damage to ecosystems (Keeley, 2009), significantly shapes the trajectory of post-fire vegetation recovery (Fernández-Manso et al., 2016b; Mitsopoulos et al., 2019) and, conditions the socioeconomic impacts (Kalogiannidis et al., 2023).

Assessing fire severity typically involves on-site evaluations utilizing comprehensive indices like the Composite Burn Index (CBI), established by Key and Benson in 2005, which is widely regarded as a standard method. Currently, advancements in technology allow for the reliable determination of burn severity with minimal effort, across various scales, utilizing remotely sensed products (e.g. Fernández-Manso et al., 2019; Nolè et al., 2023). These spectral products are often complemented by precise field data to validate them. Traditionally, vegetation indices generated from two spectral bands of multispectral remotely sensed data, primarily sourced from missions like Landsat and Sentinel-2, have served as the foundation for evaluating fire severity (Fernández-Manso et al., 2016a; Miller et al., 2009). However, previous research (e.g. Lewis et al., 2017) have highlighted several drawbacks inherent in this approach, including: 1) low model transferability (Epting et al., 2005) due to its specificity to certain sites or ecosystems (Lentile et al., 2009); 2) no optimal performance due to the constrained number of spectral bands under consideration (Lentile et al., 2009); and 3) reduced sensitiveness to spatial variations in fire impacts, especially in cases of high and moderate severities, compared to alternative methodologies (Kolden et al., 2015).

Fraction images generated through the application of Spectral Mixture Analysis (SMA) techniques (Shimabukuro and Smith, 1991), and particularly the char fraction, have emerged as a viable and valuable alternative to spectral indices in studies focused on fire-induced damage (Quintano et al., 2013; Fernández-Manso et al., 2019; Tane et al., 2018). SMA represents each pixel within a scene as a linear combination of spectra of image basic components, or endmembers. The weighting of each endmember corresponds to its abundance in the pixel (Shimabukuro and Smith, 1991). SMA, while effective, lacks the ability to accommodate variations within endmembers, where different spectra could represent the same cover (Somers et al., 2011). By the contrary, the Multiple Endmember Spectral Mixture Analysis (MESMA) approach, introduced by Roberts et al. (1998), was specifically conceived to address endmember variability by utilizing distinct spectra for each endmember class. Since then, many studies (e.g. Quintano et al., 2019, 2020; Lewis et al., 2017; Meng et al., 2017) have showed their efficacy in estimating fire severity from satellite data. The advantages of fraction images over spectral indices can be summarized as follows: 1) simpler interpretation: these images are generally easier to comprehend compared to spectral indices, due to their inherent physical interpretation (Quintano et al., 2012); 2) utilization of full spectral range: unlike spectral indices that rely only on two or three spectral bands, fraction images typically use the complete set of spectral bands (Veraverbeke et al., 2018); and 3) avoidance of calibration with field data: unlike other methods, fraction images do not necessitate calibration against field data, streamlining the process (Somers et al., 2012).

While MESMA has proven effective in successfully spectral unmixing multispectral data (Fernández-Manso et al., 2016b), the utilization of hyperspectral remote sensing data can lead to increased sensitiveness to slight differences in fire impacts on vegetation (van Gerrevink and Veraverbeke, 2021). Airborne hyperspectral sensors like Hymap or Airborne Visible and Infrared Imaging Spectrometer (AVIRIS) have already proved their usefulness in operational fire severity assessments (e.g. van Wagtendonk et al., 2004; Kokaly et al., 2007; van Gerrevink and Veraverbeke, 2021). Similarly, spaceborne spectrometers have been used to this end (e.g. Fernández-Manso et al., 2019, using Hyperion sensor onboard of the Earth Observing-1-EO-1-satellite), proving their efficacy and advantages, mainly in spatial coverage and logistical challenges, when compared to airborne sensors (Cotrufo et al., 2018; Singh et al., 2020). The PRecursore IperSpettrale della Missione Applicativa (PRISMA) mission that provides hyperspectral data spanning the range of 400 to 2500 nm is regarded as a continuation of the Hyperion sensor. PRISMA hyperspectral data has proven its usefulness to detect active fire (Thangavel et al., 2023) and map burned areas (Lazzeri et al., 2021) or fuels (Shaik et al., 2022). However, its utilization for the assessment of fire severity has been relatively limited, except for the work of Quintano et al. (2023), who demonstrated a stronger correlation between field-measured CBI values and PRISMA data as compared to Sentinel 2 data.

Land and forest managers have a critical need for information that enables them to anticipate instances of high fire severity (Mitsopoulos et al., 2019). This is imperative as high-severity fires can bring about alterations in vegetation structure and composition, leading to profound consequences on landscape dynamics and ecosystem functioning (Wasserman and Mueller, 2023). Therefore, the proactive identification of areas displaying a notable propensity for high fire severity is an essential parameter for both, pre- and post-fire management (Parks et al., 2018). This significance is particularly pronounced in wildland-urban interface (WUI) areas, where potential post-fire consequences encompass socio-economic losses stemming from damage to man-made structures, coupled with an escalated risk of human life loss. WUIs are defined as regions where human infrastructure intersects or intermingles with wildland vegetation (Ribeiro et al., 2020; Zambrano-Ballesteros et al., 2021; Molina-Terren et al., 2019). Generally, WUI areas stand as critical zones where the concentration of economic losses and fatalities occurs due to the vulnerability of populations and assets to extreme fire events that are challenging to control (Schug et al., 2023), in addition to a higher ignition and burning probability (Zigner et al., 2022; Batista et al., 2021; Modugno et al., 2016). In the context of Southern Europe, shrublands and forests are progressively encroaching upon rural areas (Molina-Terren et al., 2019), forming an interface that necessitates the adoption of different and new strategies for risk planning (Fernández-García et al., 2023) to account for the intricate dynamics at play in these areas.

Previous studies highlighted the important influence of topography, climate, weather and fuel, as well as their complex interactions in driving fire severity (e.g. Agee and Skinner, 2005; Kane et al., 2015; Storey et al., 2016, Babu et al., 2023; Malandra et al., 2022, Calheiros et al., 2022, Costa-Saura et al., 2022; Wasserman and Mueller, 2023). Parks et al. (2018) classified those drivers in spatially-variable drivers (fuel, topography, and climate), and temporally-variable drivers (fire weather and climatic extremes). Although the effect of spatially and temporally-variable drivers are generally well-investigated, there are few studies that use them to procure wall-to-wall estimates of high fire severity likelihood at regional scales (Parks et al., 2018; Fernández-Manso et al., 2019).

Our primary goal is twofold. First, we try to leverage PRISMA hyperspectral data and spatially-variable fire severity drivers, including records from National Forest Inventories (NFI), to develop a fire severity model at regional scale in the western Mediterranean Basin, with a specific emphasis on the high fire severity likelihood. NFI data represent a substantial and relevant source of information that is of crucial importance in the development of planning strategies and assessments at extensive levels in the context of European and global forest services (Kangas and Maltamo, 2009). However, the joint application of hyperspectral and NFI data in wildfire hazard analysis has so far been underutilized. Second, we aim to identify the hot-spot WUIs (or WUI areas with high fire severity likelihood) within a relatively large Spanish Mediterranean-type climate region. This approach will enable stakeholders and decision-makers to allocate resources and implement strategic interventions thereby enhancing the efficiency of fire management and mitigation efforts, as well as to facilitate the formulation of evacuation strategies aimed at safeguarding lives and properties in WUI areas.

To accomplish this double objective, we have established a structured approach encompassing three key steps:

1. **Assessment of fire severity at local scale (Sierra de la Culebra wildfire).** This initial step involves the creation of a categorized fire severity map with physical basis for this area, which has been affected by an extreme wildfire event that burned >28,000 ha of typical Mediterranean ecosystems. For this purpose, we will use PRISMA hyperspectral data, MESMA algorithm and field-based measurements of fire severity.
2. **Development of a high fire severity probability map at regional scale.** We intend to model and extrapolate at regional scale the hyperspectral-based fire severity estimates (high probability class) through spatially-variable drivers primarily extracted from each grid unit (0.01 km^2) present in the Spanish Forest Map at 1:25000 (SFM25) derived from the fourth Spanish NFI (SNFI4). For this purpose, we will use a random forest (RF) algorithm (Breiman, 2001).
3. **Building of a regional hot-spot WUIs map.** We plan to identify and characterize the hot-spot WUIs by crossing the information from the regional probability map of high fire severity and a WUI cartography at regional scale.

2. Material

2.1. Study area

Our study area is located in the autonomous region of Castilla y León (Northern-Central Spain; Fig. 1), that is the most extensive administrative region of Spain, and is among the largest in Europe, covering an area of 94,226 km^2. Its geomorphological distinctive characteristics are mostly composed by the plateau of the Iberian Peninsula, with an average altitude of about 800 m above sea level, accompanied by a mountainous contour whose peaks reach around 2500 m. The majority of the territory is drained by the Douro River (Duero in Spanish), which flows westward towards the Atlantic Ocean. Notably, the Douro River ranks as the highest-flow river on the Iberian Peninsula. According to the Köppen climate classification, the climate is catalogued as Temperate Mediterranean in most of the autonomous region (the focus areas of this study), characterized by prolonged and cold winters, with average temperatures of 3–6 °C in January, and brief but hot summers (averaging 19–22 °C). However, it presents the distinctive patterns of summer aridity typical of the Mediterranean climate, for three to four months. The average annual precipitation is 450–500 mm, worsening in the lower areas. In ecological terms, the relevance of Castilla y León in Europe is significant, since 25 % of the European Union's Natura 2000 Network is located in this region.

2.2. Sierra de la Culebra wildfire

The second-largest extreme wildfire event documented in Spain (28,046 ha burned) occurred from 15th to 19th June 2022 in Sierra de la Culebra (Northwestern Spain). Altitude in Sierra de la Culebra ranges between 747 and 1205 m a.s.l., and wide valleys and steep hillsides characterize the topography. During the spread of the fire, there were records of severe fire weather conditions (Rodrigues et al., 2023), attributed to a heat wave that was recorded from 11 to 20 June. Furthermore, a profound drought was documented during the preceding spring season leading up to the fire incident. The wildfire significantly impacted a variety of Mediterranean ecosystems, including forests dominated by *Pinus pinaster* Ait. (maritime pine) and *Pinus sylvestris* L. (Scots pine), woodlands of *Quercus pyrenaica* Willd. (Pyrenean oak) and *Quercus ilex* L. (holm oak), shrublands predominantly populated by *Pterospartum tridentatum* (L.) Willk., *Cistus ladanifer* L., *Halimium lasianthum* subsp. *alyssoides* (Lam.) Greuter, and *Erica australis* L., as well as Mediterranean grasslands. Fire was particularly extreme within shrublands and maritime pine stands, whereas it had a moderate behavior in the oak woodlands and Scots pine forests (Regional Forestry Service, personal communication).

2.3. Field data

In July 2022, approximately one month following the wildfire event, we conducted a fire severity assessment across 70 field plots of 30 m × 30 m. To carry out this assessment, we employed a slightly modified protocol of the CBI (Key and Benson, 2005). The appropriateness of these CBI adaptations has been confirmed within plant communities typical of Mediterranean regions analogous to those found in the wildfire area (Fernández-García et al., 2018; Fernández-Guisuraga et al., 2023b; Huerta et al., 2022). We followed basically the CBI protocol outlined by Key and Benson (2005) with two exceptions: 1) we omitted factors that have to be measured in extended assessments of fire severity, such as the percentage of colonizers (plants with potential dominance within 2 to 3 years after the fire newly generating from seeds dispersed over the plot), and changes in species composition (changes in relative abundance of species anticipated within 2 to 3 years postfire); and 2) we discarded medium and heavy fuel consumption indicators as these were not significantly present in our study site.

Georeferencing of plots was accomplished using a GPS receiver with a root mean square error in the X and Y dimensions ($RMSE_{X,Y}$) of <1 m. These plots were intentionally established within areas displaying uniform fire effects, thereby ensuring uniform spectral responses for analysis. Following Congalton and Green (2009), a randomly stratified sampling scheme was adopted to take into account the variability in forest species composition. The dominant plant communities were used

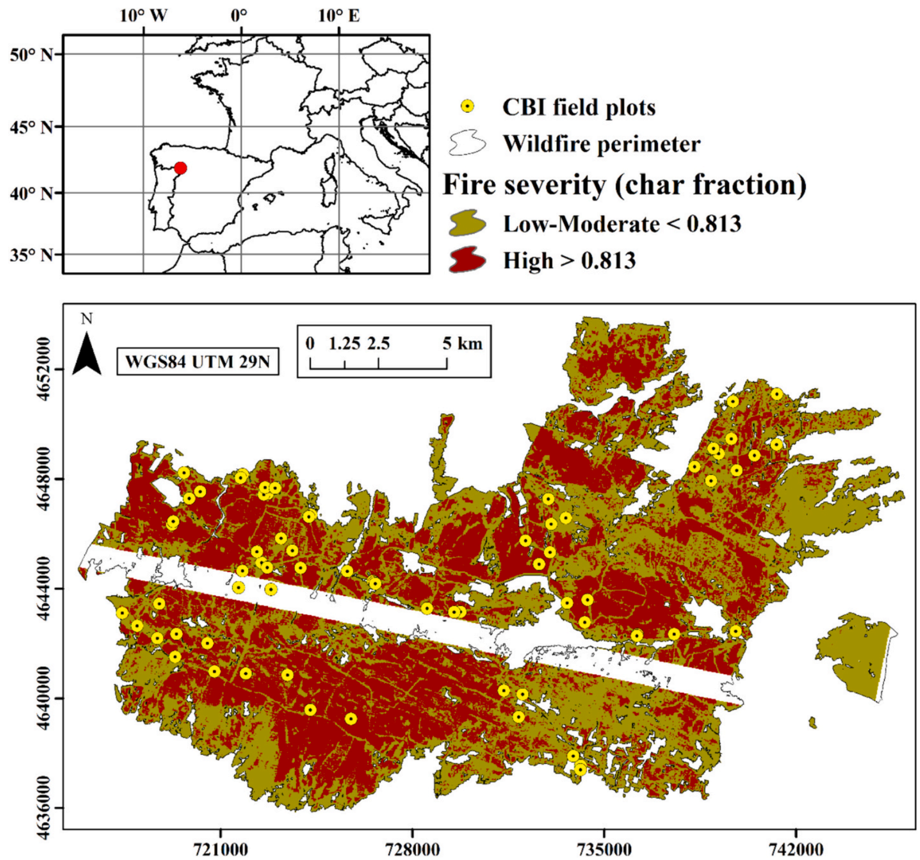

Fig. 1. Location of Sierra de la Culebra wildfire and Composite Burn Index (CBI) field plots. We show the categorized fire severity map derived from PRISMA shade-normalized char fraction image calculated using Multiple Endmember Spectral Mixture Analysis (MESMA).

as strata, with grasslands being excluded from consideration. During data collection, specific attributes were recorded for each stratum. For the understory layer, attributes such as char characteristics of the substrate and fine fuel consumption were documented. In strata encompassing herbs, low shrubs, and trees under 1 m in height, as well as those comprising tall shrubs and trees ranging from 1 to 5 m, the percentage of consumed foliage was recorded. For the overstory layer, encompassing intermediate trees measuring 5 to 20 m and those towering over 20 m, observations entailed recording of the proportions of brown, green, and black foliage, along with the char height on the tree trunk. The robustness of measurements was ensured by requiring consensus from at least two observers, a practice aligned with de Santis and Chuvieco (2007). CBI value was subsequently calculated as the mean of rating grades obtained across all strata.

2.4. Satellite data

PRISMA, is a spaceborne hyperspectral mission that has a temporal resolution of 29-day, a spatial resolution of 30 m, and possesses a swath spanning 30 km (Cogliati et al., 2021). Equipped with push-broom Visible and Near-Infrared (VNIR) and Shortwave Infrared (SWIR) spectrometers, PRISMA captures spectral data across 240 bands (bandwidth < 15 nm) ranging from 400 to 2500 nm. On 13 July 2022, an on-demand PRISMA satellite scene encompassing the wildfire study site was acquired under optimal no-cloud condition. We downloaded the Level 2D product (bottom-of-atmosphere orthorectified product corrected for atmospheric effects) (ASI -Italian Space Agency-, 2020; Pignatti et al., 2022) from the mission server (https://prisma.asi.it/).

2.5. National Forest Inventory data and ancillary data

SNFI4 provides information at regional and national level on the state and evolution of Spanish forests, and the SFM25 constitutes the cartographic basis of the SNFI4. Both have continuous nature and a periodicity of at least decennial updating. Functioning as Spain's fundamental forest cartography on a national scale, SFM25 encompasses the spatial distribution of the country's forest ecosystems, and provides information by grid unit on structural types, fuel models, primary land-use, dominant tree and shrub species, and fractional cover by life forms, among other attributes. The minimum grid unit within SFM25 is 0.01 km^2 (Alberdi et al., 2010).

As ancillary data we considered: (i) Global Aridity Index (AI) dataset v3 (Global-AI_PET_v3; Zomer et al., 2022) that offers 30 arc-seconds global raster data; (ii) a digital terrain model created from LIDAR point clouds and provided by the Spanish Aerial Ortho-photography National Plan (PNOA-DTM) with a 25-m grid size. The PNOA-DTM was used to compute all topo-climatic variables except for the AI; (iii) the SFM25 and 50-cm PNOA orthophotos were used to delineate polygons in the PRISMA imagery from which to extract potential endmembers to be used in the MESMA procedure; (iv) National Topographic Base 1:25,000 (NTB25), sourced from the Spanish National Geographic Institute (CNIG, 2022), was used to identify buildings and map WUI areas at regional scale.

3. Methods

3.1. Fire severity mapping of Sierra la Culebra wildfire using PRISMA hyperspectral data

The fire severity map of the extreme wildfire event in Sierra de la

Culebra was based on the PRISMA hyperspectral image following three steps: preprocessing of the PRISMA image, MESMA procedure, and classification of the obtained PRISMA shade-normalized char fraction image (Quintano et al., 2023).

3.1.1. Preprocessing of the PRISMA image

The hyperspectral cube of the downloaded PRISMA scene was created by combining visible and near-infrared (VNIR) with shortwave infrared (SWIR) bands giving priority to SWIR bands overlapping the VNIR range. Bands that are sensitive to water vapor absorption, or showing a low signal-to-noise ratio and artifacts were excluded (Amici and Piscini, 2021). A portion of the PRISMA scene along the central axis of the wildfire exhibited anomalous reflectance data due to an in-orbit sensor calibration failure and was thus discarded.

3.1.2. MESMA procedure

We analyzed the PRISMA image of the Sierra de la Culebra wildfire through a MESMA-based approach in a previous study (Quintano et al., 2023), and thus we include here a brief summary of the MESMA procedure, which has in turn two stages: spectral library building and spectral unmixing. Both steps were accomplished by the Visualization and Image processing for Environmental Research (VIPER) tools 2.1 software (Roberts et al., 2019). The spectral library building involved the identification of endmember spectra (pure spectral signatures representing a specific material or surface present in the scene), and their inclusion into a spectral library (Shimabukuro and Smith, 1991). Specifically, the PRISMA scene was spectrally unmixed using as endmembers: char, photosynthetic vegetation (PV), non-photosynthetic vegetation (NPV) and soil (Quintano et al., 2013, 2017, 2020). This iterative step provided distinct fraction images for each of the endmembers under consideration (Roberts et al., 1998). Finally, the char fraction image was shade-normalized to remove the influence of the shade fraction (Roberts et al., 2019). For more information see the MESMA procedure section in the Supplementary Material and Quintano et al. (2023).

3.1.3. Classification of PRISMA shade-normalized char fraction

We used thresholds to classify the PRISMA shade-normalized char fraction into fire severity classes following the method proposed by Key and Benson (2005) to categorize delta Normalized Burn Ratio (dNBR) index. First, the values of the shade-normalized char image fraction were extracted for every 30 m × 30 m CBI plot accounting for the distribution of several pixels inside each plot (Picotte and Robertson, 2011). Second, a linear regression model between field-measured CBI and shade-normalized char fraction values was calibrated. The performance of the model was evaluated using the coefficient of determination (R^2). Third, CBI values were categorized into two levels of fire severity. To this end, the CBI thresholds proposed by Miller and Thode (2007) were considered in this study: low-moderate severity (CBI $\leq$ 2.25) and high severity (CBI $>$ 2.25). These specific CBI thresholds were selected due to their widespread acceptance globally (Fernández-Manso et al., 2016b; Kane et al., 2014; Stambaugh et al., 2015), and their alignment with fire effects in Mediterranean ecosystems (Quintano et al., 2017; Fernández-Guisuraga et al., 2023a). Finally, we derived shade-normalized char fraction thresholds from the CBI thresholds using the linear regression model. We considered low-moderate and high fire severity classes since areas burned at high severity are a priority in the definition of post-fire emergency actions and may pose a high threat to WUI areas (Cocke et al., 2005; Beltrán-Marcos et al., 2023).

3.2. Regional fire severity modelling: map of high fire severity probability

We used a Random Forest (RF) classification algorithm (Breiman, 2001) to assess the capability of several spatially-variable drivers to predict categorized fire severity data. The RF algorithm was selected mainly for two reasons: 1) RF indirectly addresses spatial autocorrelation by building multiple decision trees on random subsets of data. Each tree is constructed using a random subset of features and observations, reducing the impact of spatial structure in the data (Cutler et al., 2007); and 2) RF captures non-linear relationships by constructing multiple decision trees. Each tree divides the feature space into regions using binary decisions based on feature thresholds. By combining predictions from multiple trees, RF algorithm can model complex non-linear relationships, making it suitable for a wide range of predictive tasks where relationships between variables are intricate and non-linear (García-Llamas et al., 2020; Fernández-Guisuraga et al., 2022). Additionally, the algorithm offers other advantages such as efficient computation times, robust performance across different applications, and the provision of accuracy information during the classification process (Rodríguez-Galiano et al., 2012; Wang et al., 2019).

3.2.1. RF input variables

We included as predictors of categorized fire severity data in the RF algorithm two types of spatially-variable drivers: pre-fire fuel type and structure, and topo-climatic variables. The six variables related to pre-fire fuel (total cover, tree cover, shrubs cover, herbs cover, shrubs height, and ecosystem type) were directly extracted from the SNFI4/SFM25 grid unit (Table 1). As topo-climatic variables, we considered (Table 1): Aridity Index (AI), Heat Load Index (HLI), slope (Horn, 1981), Topographic Position Index (TPI), Topographic Ruggedness Index (TRI), and Topographic Wetness Index (TWI). The AI was computed as the ratio between precipitation and the FAO-56 Penman-Monteith Reference Evapotranspiration (ET_0). Essentially, it denotes the comparison between rainfall and vegetation water demand, aggregated on an annual basis. Within this formulation, higher AI values correspond to more humid conditions, while lower values indicate more arid conditions. The HLI was used as a proxy for evapotranspiration and soil temperature. It was computed following McCune and Keon (2002). The TPI compares the elevation of the target pixel with that of the neighboring pixels. Positive values indicate that the target pixel is located higher than its average surroundings, indicating potential fuel convective pre-heating. The TRI is a proxy for topographic complexity and dissected terrain (Riley et al., 1999). Finally, the TWI is related to topographic convergence and reports the potential of an area to evacuate or retain water (Gessler et al., 1995). All topo-climatic variables except the AI, acquired from the Agroclimatic Atlas of Castilla y León (https://www.atlas.itacyl.es/), were calculated in R (R Core Team, 2021) using the "raster" (Hijmans, 2023) package. These variables were resampled to the grid of the PRISMA char fraction image (30 m) using the nearest neighbor algorithm. Fire severity estimates and topo-climatic variables were summarized for each SMP25 grid unit.

3.2.2. RF algorithm

RF classification algorithm was used to predict categorized fire severity data based on PRISMA char fraction image (dependent variable) using pre-fire fuel and topo-climatic variables (independent variables). The Boruta feature selection algorithm (Kursa and Rudnicki, 2010), designed as a wrapper around RF, computes permutation test and uses variable importance measures to determine important and non-redundant features within the predictors' dataset. Subsequently, the RF classification algorithm was calibrated from the selected Boruta features. To ensure RF prediction stability, the *ntree* model hyperparameter was set to 2000 (Probst and Boulesteix, 2018). The optimum value of the *mtry* hyperparameter was found by tuning through repeated 10-fold cross-validation ten times. RF classification achievement was assessed by a 10-fold cross validation repeated 10 times. Kappa index, overall accuracy (OA; %), user's accuracy (UA; %) and producer's accuracy (PA; %) for each fire severity category computed from the average confusion matrix were used to measure the accuracy of classification. We also computed partial dependence plots for each predictor in the RF model. Following the convention of Hastie et al. (2009), we used the logit scale for the partial dependence calculation in machine-learning models. For each k level of fire severity categorical response, we compute:

$$f_k(x) = log[p_k(x)] - \frac{1}{K}\sum_{k=1}^{K} log[p_k(x)], k = 1, 2, \ldots, K,$$

where x is the predictor for which partial dependence is sought, and $p_k(x)$ is the predicted probability of the k-th class. Partial dependence plots of $f_k(x)$ depict the dependence of the log-odds for the k-th class on different subsets of the x input variables (Greenwell, 2017). Although p_k is the proportion of votes for class k in RF models and cannot be interpreted as underlying distributional probabilities, we refer to them as class probability estimates by a stretch of terminology (e.g. Breiman, 2001; Hastie et al., 2009; Greenwell, 2017) throughout the manuscript. We show for each predictor in the RF model the partial dependence plots exclusively for the target high fire severity class.

RF model object was used to generate a spatial prediction of high fire severity probability at regional scale. All analyses were conducted in R (R Core Team, 2021) using the "RandomForest" (Liaw and Wiener, 2002), "Boruta" (Kursa and Rudnicki, 2010), "caret" (Kuhn, 2020), "pdp" (Greenwell, 2017) and "raster" (Hijmans, 2023) packages.

3.3. Map of regional hot-spot WUIs

Since there is no standard procedure for the definition of WUIs in Europe, and based on previous research in the Iberian Peninsula (Beltrán-Marcos et al., 2023; Fernández-García et al., 2023), the spatial characterization of WUIs was based on buffers of fixed distance from buildings. Determination of distances around populated areas to define WUIs exhibits substantial variability in the western Mediterranean Basin, primarily influenced by distinct local regulations (Beltrán-Marcos et al., 2023; Bento-Gonçalves and Vieira, 2020). We opted to employ the most rigorous delineation strategy, which involves implementing larger buffer zones extending up to 200 m around buildings. This approach aligns with practices adopted across various European nations and is widely recognized (Lampin-Maillet et al., 2010, 2011; Lampin-Maillet and Bouillon, 2011). By doing so we guaranteed a comprehensive coverage of areas characterized by an elevated susceptibility to wildfires, a particularly critical consideration in the prevailing era marked by significant disruptions in fire regimes (Modugno et al., 2016). Thus, we designated as WUIs areas encompassing a 200-meter radius around buildings, intersecting with vegetated areas. Mapping of buildings (industrial, residential, agricultural and public) was accomplished utilizing NTB25 data and information from the Spanish national cadaster, which is generated and maintained by Public Administrations in Spain.

Our study is focused exclusively in Mediterranean-type climate areas of Castilla y León region. As the Northern part of the autonomous region of Castilla y León cannot be considered as Mediterranean, the high fire severity probability map was masked using the biogeographical regions (BGR) specified in the Code List for Bio-geographical Regions, Europe 1:50,000 (European Environment Agency, 2011). BGRs are defined as large areas of the earth's surface, delineated primarily on the basis of natural vegetation, that share distinctive ecological characteristics. Once WUI areas of Mediterranean Castilla y León region were mapped, they were crossed with the high fire severity probability map procured by means of the RF algorithm to obtain a regional hot-spot WUIs map. Finally, we fitted a one-way ANOVA and a subsequent Tukey Honestly-significant-difference (HSD) post-hoc tests to evaluate the differences in WUI area (ha) and high fire severity probability between WUI-dominant ecosystem types. Statistical significance was defined at 5 %.

Table 1
Input variables considered in the Random Forest (RF) classification algorithm.

Group	Source	Variable	Abbreviation	Unit
Fire severity	PRISMA satellite	MESMA shade-normalized char fraction	*char*	–
Pre-fire fuel variables	SNFI4/ SFM25	Total cover	–	%
		Tree cover	–	%
		Shrubs cover	–	%
		Herbs cover	–	%
		Shrubs height	–	m
		Ecosystem type	–	–
Topo-climatic variables	Global-AI_PET_v3	Aridity index	*AI*	%
	PNOA DTM	Heat Load Index	*HLI*	MJ cm^{-2} $year^{-1}$
		Slope	–	°
		Topographic Position Index	TPI	–
		Topographic Ruggedness Index	TRI	–
		Topographic Wetness Index	TWI	–

SNFI4/SFM25: fourth Spanish National Forest Inventory/Spanish Forest Map 1:25,000; Global-AI_PET_v3: Version 3 of the Global Aridity Index and Potential Evapotranspiration database; PNOA DTM: Digital Terrain Model of the Spanish National Aerial Orthophotography Plan.

4. Results

4.1. Fire severity mapping of Sierra la Culebra wildfire using PRISMA hyperspectral data

Candidate endmembers for PRISMA image unmixing were extracted from the most representative ground cover classes: (i) PV: forests and woodlands dominated by *Quercus* sp., *Pinus pinaster* and *Pinus sylvestris* forests, grasslands, shrublands, and irrigated croplands; (ii) NPV: dry grasslands; (iii) SOIL: soils, roads, urban areas, and open mines; (iv) WATER: dams and rivers; and (v) CHAR: high, moderate and low fire severity legacies. The combination of the automated IES algorithm along with the MASA, CoB, and EAR indices facilitated the selection of the most suitable spectra for constructing the definitive spectral library.

Different unmixing trials were conducted to unmix the PRISMA image, involving the adjustment of both the hierarchical level of the spectral library and the quantity of endmembers incorporated. The minimal quantity of unclassified pixels, which amounted to only 1.45 %, was attained when employing 3- and 4-endmember models within hierarchical level 3, (see Quintano et al., 2023 for more detail). In this configuration, all the endmembers from the final spectral library were included, excluding those associated with the water class. The shade-normalized char fraction image derived from PRISMA hyperspectral data (Fig. 2) effectively distinguished between areas that had been affected by the fire and those that remained unburned within the fire perimeter, showing low noise in unburned areas outside the fire perimeter.

From the linear regression model between the CBI field measurements and the PRISMA shade-normalized char fraction values (R^2 = 0.72; Fig. SM1 of the Supplementary Material) we derived the shade-normalized char fraction thresholds corresponding to the CBI thresholds. In particular: (i) low-moderate fire severity: shade-normalized char fraction $\leq$ 0.813; and (ii) high fire severity: shade-normalized char fraction $>$ 0.813 (Fig. 1).

4.2. Regional fire severity modelling: map of high fire severity probability

All pre-fire fuel and topo-climatic variables included in Table 1 were non-redundant and deemed as relevant predictors by the Boruta

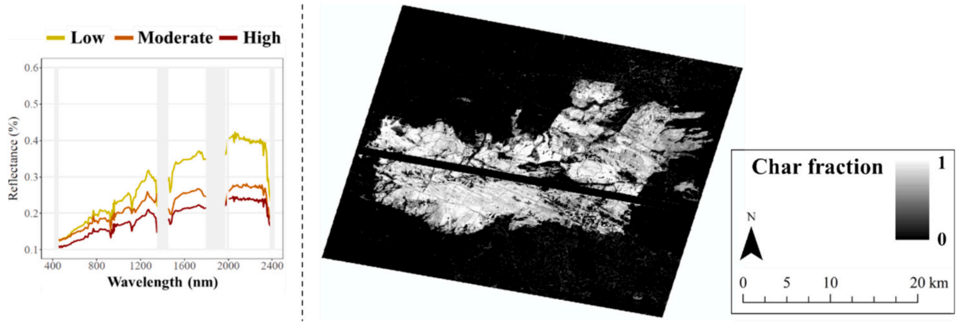

Fig. 2. Left: PRISMA representative char spectra. Bands belonging to water vapor absorption regions, or showing a low signal-to-noise ratio and artifacts were removed and represented by gray bars in the graph. Right: shade-normalized char fraction.

algorithm since they featured higher importance than the "*shadowMax*" internal variable created by the algorithm as a reference (Fig. 3). Cover by vegetation type was more important than total cover in determining the high fire severity likelihood. The most important pre-fire fuel variables corresponded to shrubs cover and height, as well as ecosystem type. Among the topo-climatic variables, the most important were slope and AI. Using all the candidate predictors, the accuracy of the RF classification model was remarkably high (OA = 91.58 % and Kappa = 0.79). PA and UA values for each fire severity category were also very high (between 80 % and 96 %), even for the high severity class of interest (PA = 89.52 % and UA = 79.73).

The relationships between the most important pre-fire fuel and topo-climatic quantitative variables, and high fire severity probability on a logit scale, were strongly non-linear (Fig. 4). High fire severity probability increased gradually with shrub cover. Shrub height showed the same positive relationship but reached a maximum probability between 1 and 1.5 m, which may be related both to the shrub height threshold needed to trigger the crowning process in forest ecosystems, and to interactions with other predictors in the RF models. The relationship between high fire severity probability and tree cover was strongly positive from 75 % onwards. Slope showed a positive relationship with high fire severity probability up to 5–10°, while it was insensitive to increases in slope above those values. Similarly, high fire severity potential increased markedly with AI values above 0.9, which can be indicative of humidity conditions conducive to high fuel build-up. Fire severity was insensitive to AI values >1 probably due to limitations imposed by excessively humid conditions for more extreme fire behavior despite increasing fuel load. Regarding pre-fire fuel type, the only categorical pre-fire vegetation predictor variable, results showed that conifer forests and shrublands were prone to the high fire severity, while grassland and crops showed the opposite behavior.

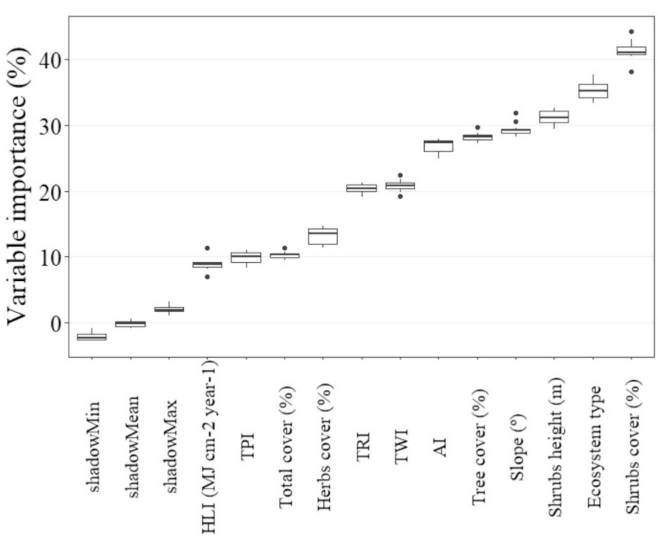

Fig. 3. Ranking of pre-fire fuel and topo-climatic variable importance as determined by the Boruta algorithm. All variables were deemed important (variable importance higher than the "*shadowMax*" internal variable). The box ranges from the first quartile to the third quartile of the distribution, and the range represents the interquartile range (IQR). The median is indicated by a line across the box. Each whisker extends to the furthest data point within 1.5 times the IQR.

4.3. Map of regional hot-spot WUIs

High fire severity probability in Mediterranean-type climate areas of Castilla y León increases in the mountainous areas of Western, Eastern and Southern extremes of the region, where we identified hot-spot WUIs with high fire severity probabilities >0.8 (Fig. 5). Conversely, high fire severity probability is rather low in the central part of the region, where crops predominate. The number of WUIs in Castilla y León was 33,616, occupying a surface area of 15,408.25 km^2. The mean high fire severity probability in WUI areas was 0.31. When crops were excluded, the mean high fire severity probability increased to 0.42. The number of WUIs whose high fire severity probability is higher than 0.5 was 4753 (covering 1719.56 km^2; 14.13 % of the total WUI area). The number of hot-spot WUIs (probability higher than 0.8) was 961 (covering 230.59 km^2; 2.86 % of the total WUI area).

The predominant fuel types in WUI areas in Castilla y León at the regional scale are grassland and crops, while there are no significant differences in the area occupied by other ecosystem types. However, the highest probability of high severity occurs in WUI areas dominated by coniferous forests, followed by shrublands (Fig. 6), which would be priority areas for intervention to mitigate the risk to local populations.

5. Discussion

5.1. Fire severity mapping of Sierra la Culebra wildfire using PRISMA hyperspectral data

Our study confirms that hyperspectral data from the PRISMA spaceborne spectrometer provide accurate estimates of post-fire char fraction as a unique predictor of wildfire severity through MESMA approach. The significance of these results is amplified by the growing accessibility of spaceborne hyperspectral missions, which goes beyond PRISMA. These missions include Hyperspectral Imager Suite (HISUI), Earth Sensing Imaging Spectrometer (DESIS) and NASA Earth Surface Mineral Dust Source Investigation (EMIT) on the International Space Station (ISS), EnMAP, or AHSI on the GF-5 satellite, as well as the forthcoming Copernicus Hyperspectral Imaging Mission for the Environment (CHIME) and NASA Surface Biology and Geology (SBG) missions. Indeed, these missions collectively represent a significant advancement in our capacity to comprehend wildfire impacts in the ecological and socioeconomical dimensions.

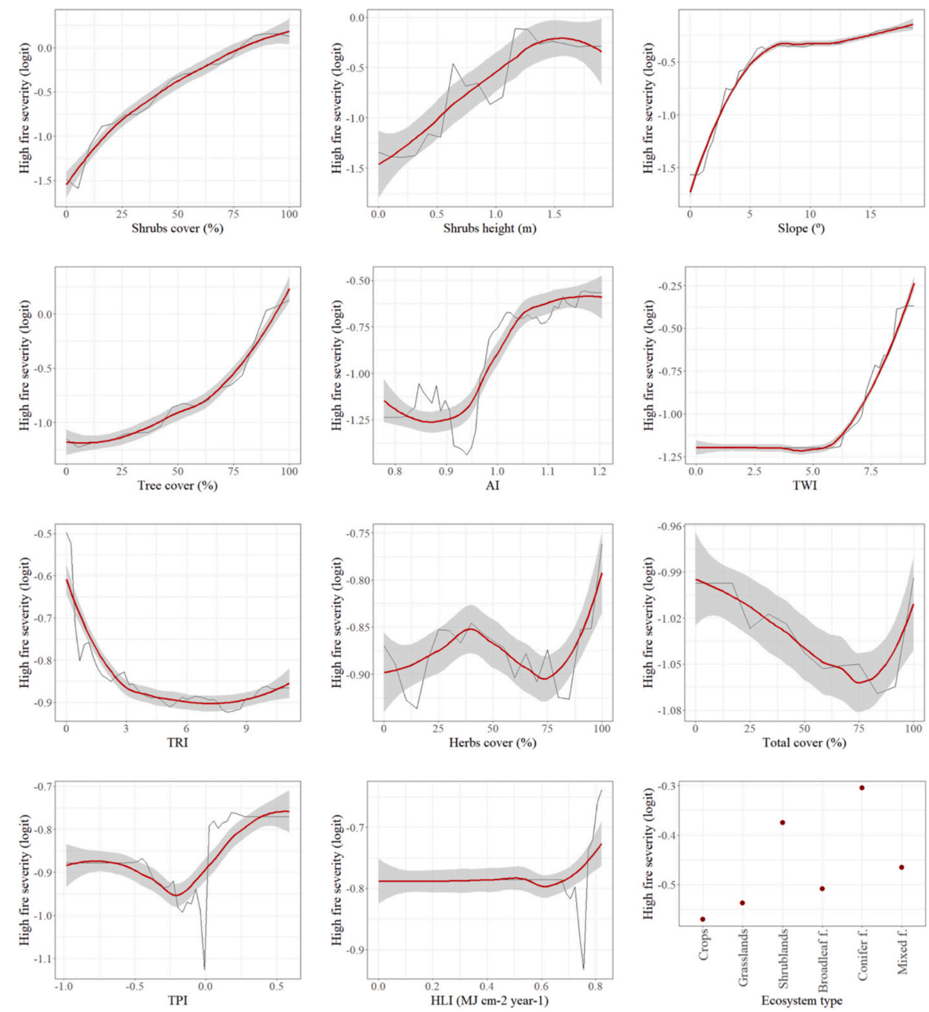

Fig. 4. Partial dependence plots depicting the relationship between the probability of high fire severity outcome on a centered logit scale and the variability of pre-fire fuel (type and structure) and topo-climatic variables in the Random Forests (RF) classification algorithm. The red line for continuous variables is a locally weighted smooth (LOESS) curve. Partial dependence calculation depicts the dependence of the log-odds for the high fire severity class on different subsets of the input variables. Although the proportion of votes for class *k* in RF models cannot be interpreted as underlying distributional probabilities, we call these class probability estimates by a stretch of terminology (e.g. Breiman, 2001; Hastie et al., 2009; Greenwell, 2017) throughout the manuscript.

The high accuracy procured in the relationship between CBI and PRISMA char fraction values in the Sierra de la Culebra wildfire can be attributed to the higher spectral dimensionality inherent to hyperspectral data as compared to broadband data (van Wagtendonk et al., 2004; Veraverbeke et al., 2018). These findings align with previous research using airborne spectrometers with reduced coverage but higher spatial resolution than spaceborne missions. Veraverbeke et al. (2014) reported that AVIRIS char fraction showed a stronger correlation with the geometrically structured CBI (GeoCBI) than Landsat estimates ($R^2 = 0.86$ versus $R^2 = 0.65$, respectively) over the Canyon Fire in California. Tane et al. (2018) also reported a notably high correlation between MESMA char fraction image derived from AVIRIS data and GeoCBI values ($R^2 = 0.74$) mapping fire severity after the 2013 Rim Fire in California. Despite the well-recognized benefits of MESMA fraction images retrieved from hyperspectral over multispectral data, the greater availability of multispectral images for management purposes is noteworthy. For this purpose, land managers could still obtain acceptable local-level estimates of char fraction images as a proxy for fire severity (Fernández-Manso et al., 2012, 2016a, 2016b; Quintano et al., 2013, 2017, 2020) but at the cost of reduced generality and increased endmember collection efforts (Quintano et al., 2023).

5.2. Regional fire severity modelling: map of probability of high fire severity

Though many researchers assessed fire severity from a variety of approaches in recent years (Miller et al., 2012; Estes et al., 2017; Picotte et al., 2020; Leblon et al., 2022; Arkin et al., 2023; among others), few of them have created maps depicting probability of high fire severity (e.g. Keyser and Westerling, 2017; Parks et al., 2018); and most of these studies have focused on limited geographic areas, from single fires to small-sized regions (Dillon et al., 2020). Keyser and Westerling (2017) conducted a mapping of high fire severity probability across the western United States, though with a limited spatial resolution (12 km). Their study primarily focused on investigating the influence of interannual climate variability on high-severity fire potential. Parks et al. (2018) also carried out a mapping of probability of high fire severity in the Western United States, but their analysis exclusively considered forested environments. Dillon et al. (2020) estimated the spatial distribution of high fire severity across United States, providing valuable insights that can inform decision-making and research efforts related to fire severity in several ecosystems. Our study used a machine learning algorithm from which we generated wall-to-wall estimates of high fire severity probability at regional scale leveraging for the first time the fourth revision of Spanish NFI data and the derived SFM25, which represent an

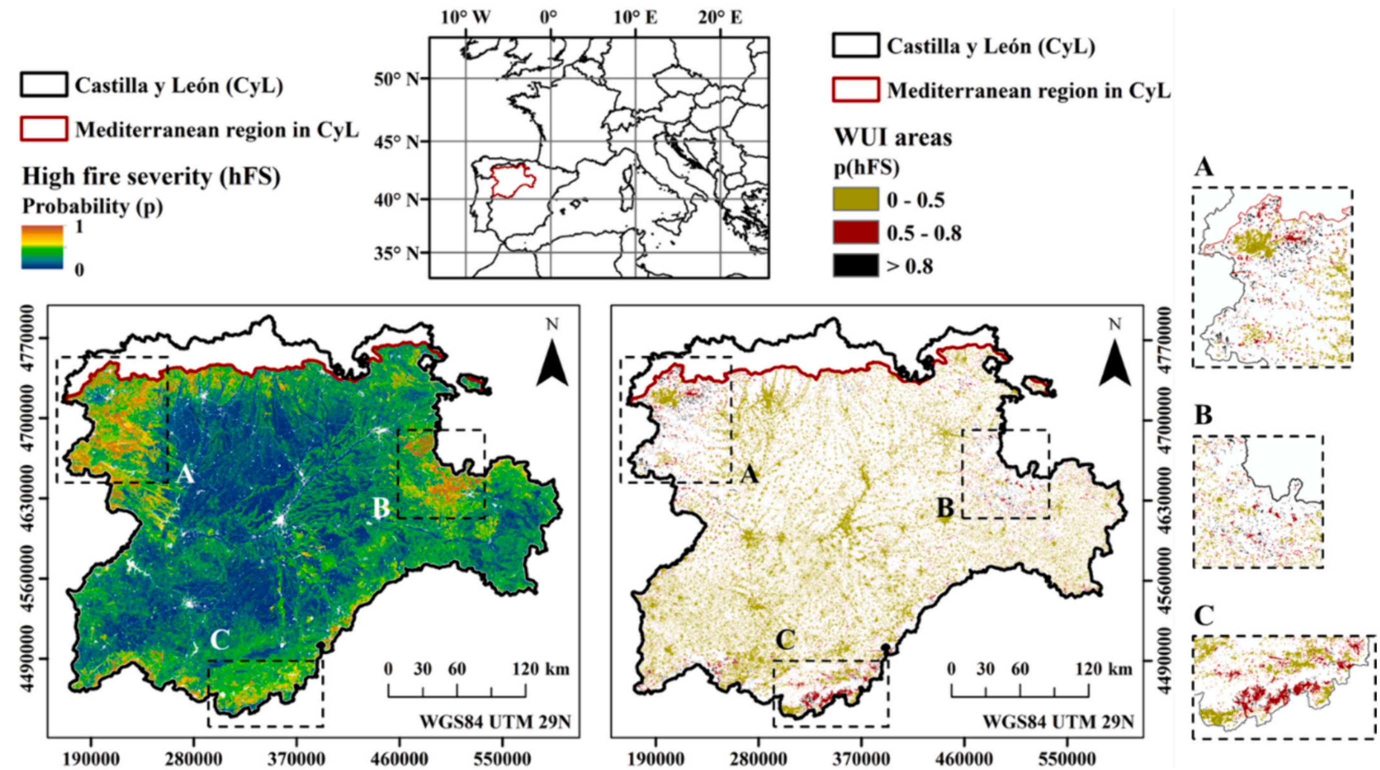

Fig. 5. Upper: location map of study area. Left: wall-to-wall predictions of high fire severity probability at regional scale in Mediterranean-type climate areas of Castilla y León; Right: map depicting the location of WUI areas and their probability of high fire severity. We show detail zoom of three hot-spot WUI areas: A-north-west; B-east; and C-south.

unbiased, spatially-explicit and comprehensive source of many stand variables throughout the complete range of Mediterranean ecosystem types of interest (Álvarez-González et al., 2014).

In our study, the four most important predictors of fire severity were related to pre-fire fuel variables (shrub cover, ecosystem type and shrub height) and topography (slope). The most relevant climatic predictor was AI which ranked sixth on decreasing order of importance. These results emphasize the role of land cover and fuel characteristics in shaping fire behavior. Previous studies also reported the relevant role of vegetation cover and vegetation amount in mapping fire severity at regional scale in Western Italy (Costa-Saura et al., 2022). Similarly, Dillon et al. (2020), indicated that vegetation-related variables emerged as the most reliable fire severity predictor in western United States, followed by elevation and fuel moisture. We did not include elevation in our model because it was directly related to ecosystem type, which was included and ranked second in model importance. The findings reported by Beltrán-Marcos et al. (2023) are also aligned with our results. They identified land cover class, that can be considered equivalent to the ecosystem type variable in this study, as the primary factor driving fire severity, followed by fractional vegetation cover, which is conceptually related to shrub and tree cover variables used here. Shrublands, along with coniferous forests, were very prone to high-severity fire, in agreement with previous studies that found that these fuel types, due to their flammability and structure, pose a major threat to human settlements in productive environments of the western Mediterranean Basin (e.g. Fernández-Guisuraga et al., 2021; Rodriguez-Jimenez et al., 2023). We found that shrub height was also an important predictor in determining fire severity outcome, since it is well-known that this variable will dictate the triggering of the crowning process in forest ecosystems dominated by ladder fuels and low canopy base heights (Fernández-Guisuraga et al., 2021). Our findings appear to deviate from earlier research (Birch et al., 2015; Estes et al., 2017) that emphasized the importance of topography in influencing fire severity. However, it is essential to consider that topography often serves as an indirect proxy of vegetation and fuel distribution. In this context, our results appear to align more closely with the conclusions drawn by Parks et al. (2018), which suggest that pre-fire fuel load plays a more crucial role than inherent topographic factors in shaping fire behavior. Nonetheless, our findings also indicate that topographic variables slightly contribute to the predictive power of the RF model, suggesting that topography can still be a relevant factor in disentangling fire severity role when considered in conjunction with pre-fire fuel variables. Although fire weather is an important control on fire behavior in Mediterranean ecosystems (e.g. Birch et al., 2015; Lydersen et al., 2017), we did not consider fire weather-related variables because they vary not only in space, but also in time (Parks et al., 2018), and distinct fire weather datasets for different dates are not available for the Sierra de la Culebra wildfire in which local fire severity estimates are calibrated. The high fire severity probability product at regional scale may be representative of fire danger under severe weather conditions recorded in the area, and under which most extremes wildfires burn (Parks et al., 2018). However, it must be considered that short-term (hourly to daily) fluctuations in fire weather-related variables such as relative humidity, wind speed and temperature, may significantly influence fire behavior along different times of wildfire progression (Ruffault et al., 2016). In fact, high severity patterns within wildfire perimeters may be concentrated mainly in those areas burned under extreme fire weather conditions (Moritz, 1997), which is particularly relevant under drought-driven fire regimes where bottom-up fire behavior drivers may play a secondary role in determining fire severity (Oliveras et al., 2009). The influence of these fire-weather feedbacks on the determination of hot-spot WUIs at regional scales should be considered in future studies.

Our results revealed that high fire severity probability is concentrated in a relatively small portion of the studied region, primarily within the most mountainous and forested areas. Conversely, the central plateau, which is mainly dedicated to crops, exhibits a low probability.

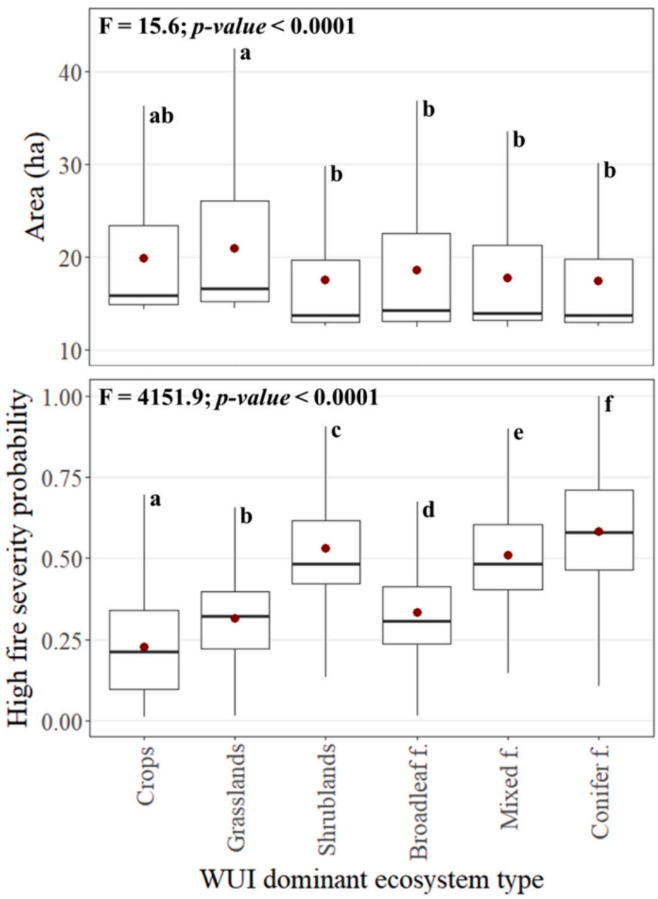

Fig. 6. Boxplots depicting the relationships between WUI area (ha) and high fire severity probability with the WUI-dominant ecosystem types. The box ranges from the first quartile to the third quartile of the distribution, and the range represents the interquartile range (IQR). The median is indicated by a line across the box. The red point denotes de data mean. Each whisker extends to the furthest data point within 1.5 times the IQR. We showed one-way ANOVA and Tukey Honestly-significant-difference (HSD) post-hoc tests results. Lowercase letter denote significant differences at the 0.05 level.

This pattern is consistent with assessments of Monitoring Trends in Burn Severity (MTBS) data, which have indicated that typically, less than one-third of the area burned in wildfires in the western United States, including Mediterranean ecosystems, experiences high fire severity (Dillon et al., 2011; Finco et al., 2012; Picotte et al., 2016).

5.3. Map of regional hot-spot WUIs

The surface occupied by WUI areas in Castilla y León represent approximately 15 % of the region. Apart from WUIs associated with urban expansion, the majority of WUIs (located in the Central plateau of Castilla y León) result from the process of agricultural abandonment near settlements. This process enables vegetation to regenerate, creating an increased interface between vegetation and urban or developed areas (Pausas and Fernández-Muñoz, 2012; Radeloff et al., 2018; Bar-Massada et al., 2023). Over the past few decades, land abandonment has been widespread in this region (Lasanta et al., 2017), and linked to an uptick in wildfires, potentially exacerbating fire feedbacks even further (Salis et al., 2022; Ermitão et al., 2023). The combination of land-use abandonment and climate change is leading to substantial fuel accumulation in the form of shrubs and forest vegetation (Badia et al., 2019; Mantero et al., 2020), which represents a critical situation in terms of fire hazard and vulnerability (Beltrán-Marcos et al., 2023; Francis et al., 2023). This evolving landscape, mainly transitioning from agricultural lands into shrublands, where high fire severity likelihood is concentrated, presents significant challenges for pre-fire management (Pausas and Fernández-Muñoz, 2012; Badia et al., 2019).

Overlapping the information of the regional WUI and high fire severity probability maps (hot-spot WUI map), we identified that almost 3 % of WUIs in Castilla y León had a potential probability of high fire severity >0.8. Hotspot WUIs were mainly located in the forested areas of the mountains that surrounds the Central plateau. In the last decade, >75 % of burned area in Castilla y Leon was located in these areas. In particular, A-labeled zone in Fig. 5 concentrated 69 % of the burned area in Castilla y Leon from 2012 to 2022; B-labeled only a 3 %, and C-labeled, 25 % (Junta de Castilla y León, 2023). This distribution pattern of hotspot WUIs in Castilla y León visually agrees with the pattern observed in the global WUI map produced by NASA/Maryland University within the project Global Hotspots of the WUI (https://lcluc.umd.edu/projects/global-hotspots-wildland-urban-interface). Schug et al. (2023) noted that while natural grasslands may face recurrent fire events in specific regions within the WUIs worldwide, this is not a significant problem in areas where grasslands are intensively maintained as pastures. Conversely, both natural and managed forests contribute to the fuel available for fires, rendering forested areas more vulnerable to such events. This highlights the importance of land management practices in influencing the wildfire risk within WUIs, with grassland management playing a protective role and forest management requiring careful attention to reduce fire risks. In this sense, Moreira et al. (2020) have emphasized the significance of policies that prioritize investments in fire management over fire suppression efforts. They advocate for a paradigm shift in environmental management policies, measuring effectiveness based on the prevention of socio-ecological damage rather than the extent of burned areas. Our study, which identifies WUI areas prone to high fire severity, enables forest managers to prioritize areas for fuel management interventions, potentially mitigating the severity of future wildfires.

5.4. Limitations and uncertainties

While this research contributes significantly to advancing fire risk assessment methods in the Mediterranean Wildland-Urban Interface (WUI), it is crucial to acknowledge certain limitations and uncertainties associated with the study. The first ones are related to the scale and generalization. The methodology's effectiveness at a regional scale relies on extrapolation from local-scale data. The degree to which findings can be generalized across diverse WUI areas may introduce uncertainties, particularly in regions with varying ecological and climatic conditions. The accuracy of the Random Forest predictive model is subject to the quality and representativeness of the calibration data. Variability in fire severity estimates, NFI data, and topo-climatic variables may impact the model's performance, introducing uncertainties in the regional fire severity probability map. Specifically, the coarse spatial resolution of the AI product may result in a decreased capture of spatial variability and underestimation of the importance of this variable in explaining fire severity outcomes, ultimately contributing to uncertainty in the relationships between the predictors and the response variable (Meng et al., 2015). Another limitation is that the study's reliance on specific temporal snapshots of hyperspectral data and NFI records may not capture dynamic changes in vegetation, fuel loads, or land use over time. This limitation could affect the model's ability to account for temporal variations in fire risk. Additionally, while spaceborne hyperspectral data and NFI datasets offer valuable information, their resolution may not capture fine-scale variations in WUI features. This limitation could affect the identification and characterization of hot-spot WUIs, potentially impacting resource allocation and management strategies. On the other hand, the WUI spatial characterization used may be somewhat oversimplified to represent the complex distribution pattern of sparse impervious areas. For more accurate and ecologically meaningful fire severity assessments, it is advisable to move towards more sophisticated methods that account for the spatial heterogeneity and dynamic nature of WUIs. Consideration of interface and intermix areas (Radeloff et al., 2005), as well as multiclass WUI typologies (Beverly et al., 2010; Lampin-Maillet et al., 2010), could provide a more accurate characterization of these areas (Bar-Massada et al., 2023; Beltrán-Marcos et al., 2023). Finally, the identification of hot-spot WUIs is contingent upon the accuracy of the regional high fire severity probability map and the WUI cartography. The effectiveness of these maps in real-world scenarios and their validation against actual fire events may introduce uncertainties. Understanding and addressing these limitations is crucial for the accurate interpretation and application of the study's findings.

5.5. Management advices

Strategic planning plays a pivotal role in wildfire prevention within WUI areas and holds significant societal benefits (Santasusagna-Riu and Ubeda-Cartana, 2021). These plans can advert the destruction of valuable natural resources during extreme wildfire events that can inflict substantial harm on both property and the environment (Molina-Terren et al., 2019). The hot-spot WUI map provides key information of geographic distribution of severe fire probability and offers an understanding of the ecological and topo-climatic conditions that drive high-severity fire effects in these areas. This, in turn, facilitates the consideration of ecological consequences in fire management and planning efforts (Dillon et al., 2020). Operational planning involves the practical, day-to-day implementation of strategies. Our research highlighted the significance of pre-fire vegetation as a critical factor influencing fire severity, a finding that aligns with the conclusions of other studies (e.g., Stevens-Rumann et al., 2016; Parks et al., 2018). Thus, the hot-spot WUIs map may serve as an initial guide for identifying suitable locations to implement landscape fuel treatments at tessellation-scale, thus helping mitigate the potential for severe fires and safeguard inhabited areas (Modugno et al., 2016; Samara et al., 2018). Applying mechanical treatments to reduce surface fuel loads, particularly excessive shrub cover (Lampin-Maillet et al., 2009; Fernández-García et al., 2023; Fernández-Guisuraga et al., 2023c), or elevating the height of the canopy base through pruning and conducting low stand-thinning operations that disrupt the continuity of ladder fuels (Kennedy and Johnson, 2014; Pastor et al., 2020; Fernández-Guisuraga et al., 2021) has the potential to mitigate the severity of wildfires in WUI areas (Beltrán-Marcos et al., 2023).

Since all these preventive actions are very costly, knowing which WUIs are more susceptible to high fire severity will help to optimally assign resources and actions (Sarricolea et al., 2020). WUI areas are diverse, and appropriate responses can vary significantly depending on the local context, either urban, suburban, rural or forested. In our study area, most of hot-spot WUIs are encompassed in rural and forest contexts. Some practical recommendations for WUIs in rural environments are: 1) to encourage traditional agricultural practices such as extensive livestock and agroforestry to reduce fuel loads in surrounding vegetation areas (García-Llamas et al., 2019a, 2019b; Sil et al., 2019); 2) to promote the implementation of prescribed burning treatments for the same purpose (Grebner et al., 2013; Kondo et al., 2022; Fajardo-Cantos et al., 2023); and 3) to improve the availability and access to water resources for fire suppression, including the installation of strategic water reservoirs and access points for firefighting equipment (Pastor et al., 2020). If the WUIs are located in forest environments, it is essential: 1) to maintain and clear roads and trails to ensure that they can serve as fire breaks and facilitate access for firefighting teams in case of emergency (Pastor et al., 2020); 2) to promote fire-smart management and reforestation with native and fire-resistant tree species to reduce wildfire impacts (Fernandes, 2013; Lecina-Díaz et al., 2023); and 3) to implement remote sensing and surveillance systems to detect early signs of fire, allowing for faster response times (Barmpoutis et al., 2020; Sakellariou et al., 2021).

5.6. Future study scopes

In this study, we focused only on the basic definition of WUI, but we could go further in future research works by identifying different WUI configurations according to their building density, population, urban or industrial typology, so that recommendations for the management of each type of hop-spot WUI can be further specified (Fernández-García et al., 2022). We only considered pre-fire vegetation characteristics, climatic and topographic variables but, high-severity fire risk in WUI areas can emerge due to a combination of other drivers such as soil characteristics (Viedma et al., 2020) and socio-economic aspects (Moreira et al., 2020; Chas-Amil et al., 2022). In the presentation of the Portuguese Large Wildfire Spread database (PT-FireSprd), Benali et al. (2023) emphasizes the complex interactions between fuels, topography and weather in determining wildfire behavior. The detailed set of fire behavior descriptors in PT-FireSprd, such as the rate of spread (RoS), fire growth rate (FGR) and fire radiative energy (FRE), may constitute a solid and physically-based tool to refine the identification of hot-spot WUIs in future studies.

Several more actions remain as opportunities for future research: (i) conduct an external validation of the regional high fire severity probability map obtained through RF algorithm. This validation process can help ensure the robustness and reliability of the model predictions; (ii) expand the high fire severity probability map to cover the entire national territory where NFI information is available; and (iii) exploring the use of hyperspectral images from alternative sensors. This would allow for more frequent data collection, enabling a more dynamic and timely assessment of fire severity.

6. Conclusions

Assessment of fire severity is crucial as it offers a structured perspective on the ecological impact of wildfires. In our study, we specifically concentrated on high severity because of the profound alterations it can bring to ecosystem values and the subsequent vegetation response. Thus, for the first time a regional map of probability of high fire severity was generated using a RF algorithm (Kappa = 0.8), trained with predictor variables primarily derived from SNFI4 data and MESMA PRISMA char fraction, which served as a proxy for fire severity. Similarly, for the first time, a regional map of hot-spot WUIs was built, showing the areas that concentrate WUIs with high probability of high fire severity in case of fire event (hot-spot WUIs) were primarily situated in forested regions along the mountainous borders of the region. The findings of our study offer fire managers valuable predictive tools for identifying priority areas with management action needs. Using tools such as the hot-spot WUI map contributes significantly to enhancing territorial resilience within WUIs through strategic and operational planning for wildfire prevention. This shift towards a more comprehensive and predictive approach represents a critical step in addressing the multifaceted challenges posed by wildfires in WUI areas. We played a role in advancing the development of next-generation fire risk assessment methods, which integrate remote sensing technologies with extensive ground-level datasets.

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CRediT authorship contribution statement

A. Fernández-Manso: Conceptualization, Funding acquisition, Investigation, Methodology, Visualization, Writing – original draft. **C. Quintano:** Conceptualization, Formal analysis, Funding acquisition, Investigation, Methodology, Visualization, Writing – original draft. **J.M. Fernández-Guisuraga:** Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology. **D. Roberts:** Conceptualization, Supervision, Writing – review & editing.

Declaration of competing interest

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.

Data availability

Data will be made available on request.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.scitotenv.2024.173568.

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