Safety Science 147 (2022) 105616

Contents lists available at ScienceDirect

Safety Science

journal homepage: www.elsevier.com/locate/safety

Integrating geospatial wildfire models to delineate landscape management zones and inform decision-making in Mediterranean areas

Marcos Rodrigues [a,d,*], María Zúñiga-Antón [c,d], Fermín Alcasena [e], Pere Gelabert [a], Cristina Vega-Garcia [a,b]

[a] Department of Agricultural & Forest Engineering, University of Lleida, Spain
[b] Joint Research Unit CTFC-Agrotecnio, Solsona, Spain
[c] University Institute of Research in Environmental Sciences (IUCA), University of Zaragoza, Zaragoza, Spain
[d] Department of Geography, University of Zaragoza, Zaragoza, Spain
[e] USDA Forest Service International Visitor Program, College of Forestry, Oregon State University, Corvallis, OR, USA

ARTICLE INFO

Keywords:
Wildfire occurrence
Initial attack
Fire transmission
Wildfire management
Mediterranean

ABSTRACT

Despite the abundant firefighting resources deployed to reinforce the fire exclusion policy, extreme events continue to cause substantial losses in Mediterranean regions. These catastrophic wildfires question the merely-reactive response, while science-based decision-making advocates for a paradigm shift towards a long-term solution to coexist with fire. Comprehensive management solutions integrate multiple efforts to minimize the number of escaped wildfires in fire ignition hotspots, restrict large fire spread across the landscape, and prevent losses to valued resources and assets. This study develops a wildfire management zone (WMZ) delineation framework to inform decision-making in fire-prone Mediterranean landscapes. First, we combined modeling outcomes of wildfire occurrence, initial attack success, and wildfire transmission to communities to segment the landscape in WMZ blocks. We assumed the worst-case scenario in terms of fire simultaneity and weather conditions to implement the models. The geospatial outcomes were assembled and classified into four primary archetypes, and we then designated the most suitable risk mitigation strategies for each management unit. The WMZs included (1) comprehensive management, (2) human ignition prevention, (3) intensive fuel management, and (4) fire reintroduction areas. Finally, we downscaled within zones to assign specific management prescriptions to the different areas. The results were presented in a set of cross-scale maps to assist in designing risk management plans and raise social awareness. The methodological framework developed in this study may be valuable to help mitigate risk in fire-prone Mediterranean areas, but also in other regions in which similar total suppression policies fail to reduce catastrophic wildfire losses.

1. Introduction

The Mediterranean landscapes have been coevolving with fires for millennia (Bowman et al., 2009; Krawchuk et al., 2009). The frequent fires, extensive livestock farming systems, scattered small plots of arable lands, and intensively managed forest patches created a finely grained cultural landscape where reduced fuel loads limited wildfire growth (Bowman et al., 2011; Camarero et al., 2019; Coughlan, 2015). However, the massive rural exodus towards big cities and industrial areas initiated in the 19th century, followed by the agricultural land consolidation plus mechanization after the second half of the 20th century, triggered a rapid fuel buildup fostering a hazardous forest continuum (Cervera et al., 2016). This process was faster in remote regions of southern European countries like Spain, where extreme weather conditions currently drive the fire regime (Lasanta et al., 2018; Pausas and Bond, 2020). As a result, extraordinary events now account for a growing number of human fatalities, forest destruction, and property losses (Molina-Terrén et al., 2019).

The fire exclusion policy implemented in the Mediterranean basin fails to reduce catastrophic losses despite the substantial resources allocated to support the total suppression of fires (Curt and Frejaville, 2018; Moreira et al., 2020; Tedim et al., 2018; Wunder et al., 2021). European countries strongly enforced this policy after the mid-80s by making the firefighting crews more professional and by greatly

* Corresponding author.
E-mail address: rmarcos@unizar.es (M. Rodrigues).

https://doi.org/10.1016/j.ssci.2021.105616
Received 7 March 2020; Received in revised form 30 June 2021; Accepted 26 November 2021
Available online 3 December 2021
0925-7535/

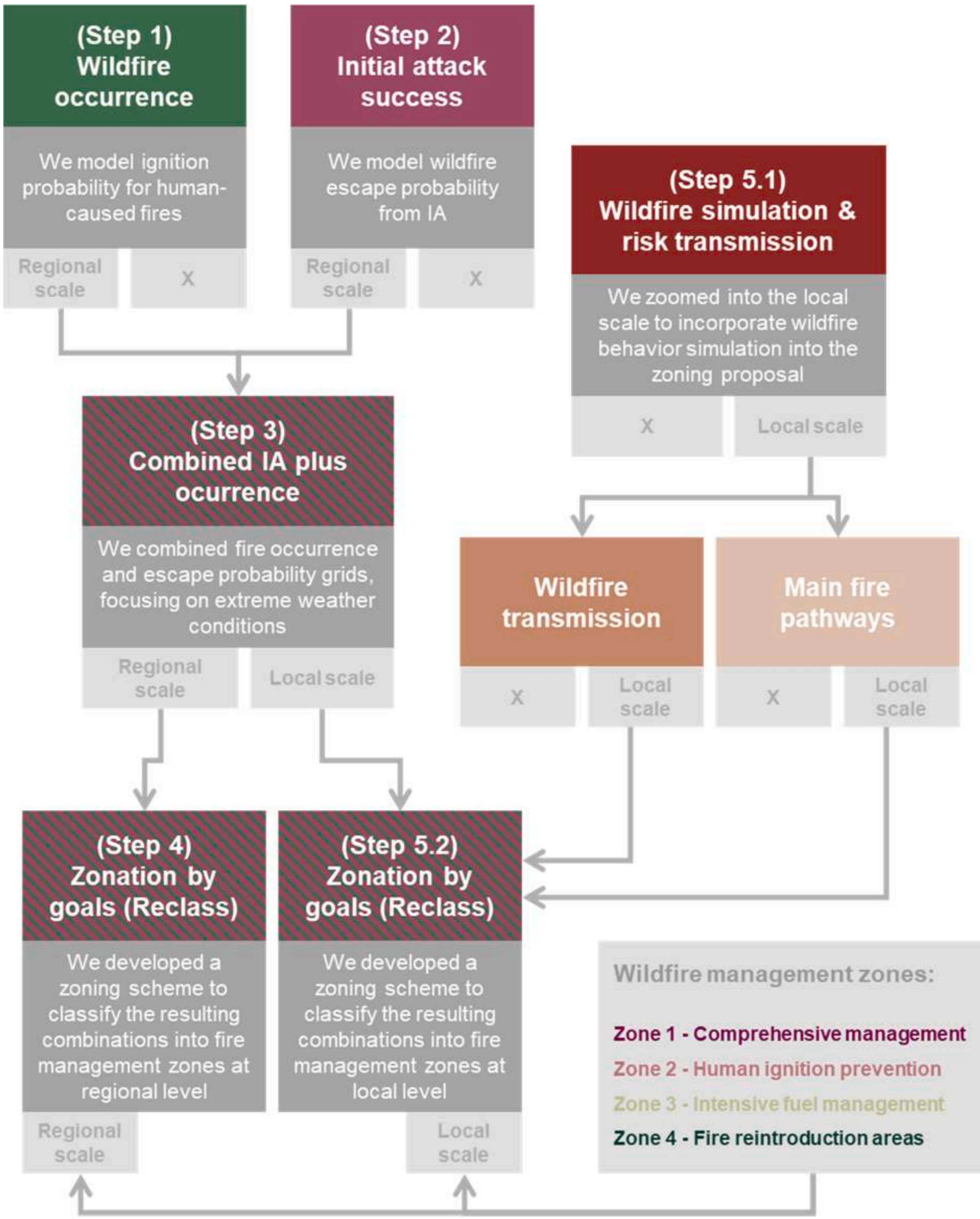

Fig. 1. Methodological workflow to integrate wildfire modeling outcomes into a zonation proposal.

increasing the aerial means (Otero and Nielsen, 2017). Paradoxically, these efforts further enhanced the fuel accumulation conducive to extreme wildfire episodes (Doerr and Santín, 2016). While the firefighting services are highly effective in suppressing most ignitions, a small number of wildfires escape, exhibiting overwhelming spread rates and very high intensities and accounting for most burned area (Fernandes et al., 2016). As a result, multiple studies advocate for 'learning to live' with fire rather than considering it an enemy, while the 'fire-smart' solutions emphasize the need for managing forest ecosystems to cope with this disturbance (Dupuy et al., 2020; Fernandes, 2013; Moritz et al., 2014; Wunder et al., 2021). In this sense, the European Union (EU) "Green Deal" program (COM/2019/640) has committed to building a climate-resilient future and set a pathway to cope with the more frequent weather extremes and unprecedented forest fires. Specifically, the EU H2020 research calls articulate the transfer of knowledge to stakeholders, where advanced wildfire models are used to provide management-oriented proactive solutions that may assist in risk mitigation planning.

Humans cause and suppress most wildfires in Mediterranean areas, and ignition locations present strong aggregation clusters with very distinctive spatiotemporal patterns (González-Olabarria et al., 2015; Salis et al., 2015). Previous studies used wildfire occurrence modeling to predict ignition probability (IP) with different methods such as logit models or random forest algorithms (Galizia and Rodrigues, 2019; Rodrigues and de la Riva, 2014) using geospatial variables correlated to anthropic factors, land cover types, topographic features, and weather conditions (Costafreda-Aumedes et al., 2017). However, only a few fires escape from initial attack (IA), which essentially depends on firefighting resource availability, deployment time or distance to fire ignitions, and fire-weather conditions (Rodrigues et al., 2019). These works presented the IP and IA success results in high-resolution maps to capture the changing patterns across the landscape and inform human ignition prevention efforts and firefighting resource allocation. At the same time, the combination of these maps provided a valuable outcome to target the areas where ignitions may trigger a large wildfire (Reimer et al., 2019).

Wildfire simulation modeling has been widely used in previous studies to predict extreme fire spread (Ager et al., 2021; Finney et al., 2011). The models require input data for escaped ignition locations, terrain, vegetation, and weather conditions to replicate observed fire size distributions and model burned areas for thousands of fire seasons assuming the most frequent wildfire season scenarios (Parisien et al., 2019). Simulated perimeters can then intersect with building footprint locations to assess fire transmission to communities and approximate the potential losses associated with long-distance spreading wildfire events (Palaiologou et al., 2018; Salis et al., 2021). Likewise, other works leveraged transmission outcomes to delineate community firesheds and prioritize fuel treatments (Ager et al., 2019). Fuel treatments indeed have been proven to be effective in restricting fire spread when implemented in strategic locations (e.g., high-transmission major wildfire pathways) at effective intensities (Espinosa et al., 2019; Salis et al., 2018) and represent a fundamental risk reduction strategy (Benali et al., 2021). Moreover, other studies also prescribed fuel treatments to generate spatial opportunities that may facilitate firefighting operations such as the backing-fire tactical use during extreme wildfires (Gonzalez-Olabarria et al., 2019).

The bulk of wildfire losses concentrate in densely populated suburban sprawl areas known as the wildland-urban interface (WUI) (Fox et al., 2015; Modugno et al., 2016). These WUI areas present intricate residential housing patterns within forest lands where the vegetation management is often poor or nonexistent (Alcasena et al., 2018b). The latest works described the built environment in terms of topographic, structural, and fuel conditions explaining the structure loss (Syphard et al., 2021; Vacca et al., 2020). Overall, these studies advocated for clearing the home ignition zone area as the primary strategy to reduce hazardous fuels and increase the defensible space for firefighters (Pastor et al., 2020; Syphard and Keeley, 2019). However, other factors, including the household's social vulnerability and the past fire experience, explained the homeowner's involvement and interest in creating fire-adapted communities (Palaiologou et al., 2021). In this sense, WUI risk maps are a very effective strategy to communicate expected fire losses and increase social awareness in risk-perception campaigns.

The present work combines developments in these three areas (fire escapes, fire models and fire losses) and bridges the gap between fire risk science and landscape management decision-making by developing a novel framework that translates and breaks down wildfire model outputs into different management zones and priority intervention areas. We pursued the double objective of (1) combining complex model outcomes and (2) prioritizing wildfire management strategies at operational scales. Similar previous works developed in Mediterranean areas are scarce, and most ignore the scenarios and strategic implications under which the total suppression policy is highly ineffective. The main novelty of this work resided in leveraging mapping science to support decision-making and enhance social risk perception in communities as encouraged in other fire-prone regions elsewhere (Gonzalez-Mathiesen et al., 2021; Wei et al., 2019). Specifically, we first assembled modeling outcomes for fire IP (Rodrigues and de la Riva, 2014), IA escape probability (Rodrigues et al., 2019), and fire transmission to communities (Alcasena et al., 2018a) to delineate different wildfire management zones (WMZs). Then, we prioritized and summarized risk reduction strategies within WMZs based on four main archetypes (Curt and Frejaville, 2018; Penman et al., 2015; Wunder et al., 2021). Ultimately, we advise a comprehensive solution where (i) human ignition prevention, (ii) fire reintroduction, (iii) fuel treatments, (iv) fire suppression, and (v) human community adaptation efforts are combined and strategically designated within a vast fire-prone cultural landscape. Our findings allowed identifying high priority WMZs, such as the areas where fires occurring under extreme conditions overwhelm firefighting capacity and expose several structures, or community firesheds requiring intensive fuel reductions due to a large fire deficit (Parisien et al., 2020).

2. Materials and methods

2.1. General workflow

The methodology was developed in 5 steps that subsequently incorporate information towards the final zoning scheme (Fig. 1). First, we calculated the probability of human-caused ignitions (step 1), and model the IA success probability under several weather scenarios (step 2). Then, we combined fire ignition and escape probability grids, focusing on extreme weather conditions (step 3). In the next stage we developed a wildfire management zone (WMZ) scheme to classify the resulting combinations into fire management zones or archetypes at regional level (step 4). The zonation arrangement pursues the optimal allocation of the following goals: (i) preventing ignitions threating assets, (ii) reintroduce and prescribe fires, (iii) optimize fuel treatment allocation, (iv) provide guidance towards fire-adapted urban and rural planning and (v) facilitate safe suppression conditions. These goals were translated into the following WMZs:

- **Zone I. Comprehensive management.** This area was assigned the highest priority for management, being candidate for interventions related to all goals except (ii) for natural fire reintroduction, since a priori conditions for fire control would be difficult, and fire presence in the landscape is already excessive (i.e., fire-surplus). Transmission source locations would be a priority for (i) ignition prevention and (v) safe suppression, but notice that also spots of high probability of ignition should be targeted by (i); both types of sites need not be coincidental in space. Source and path locations in Zone I would be preferred sites for fuel treatment (iii). Fire-adapted urban and rural planning (iv) should be implemented in the areas impacted by fires starting in the source locations, complemented by a vulnerability analysis.
- **Zone II: Human ignition prevention.** These are the landscape portions that would require a special focus on goal (i) prevent ignitions threating assets. Considering the high demands on firefighting resources placed by multiple ignitions, goal (v) facilitate safe suppression conditions, should be given due attention, at least to make sure that current levels of IA success are not lessened. The general high human risk would recommend also to (iii) optimize fuel treatment allocations and (iv) provide guidance towards fire-adapted urban and rural planning in relation to unlikely, but still possible, fire escapes.
- **Zone III: Intensive fuels management.** This zone would require to prioritize fire behavior-related and suppression goals: (iii) optimize fuel treatment allocation, (iv) provide guidance towards fire-adapted urban and rural planning and (v) facilitate safe suppression conditions. However, (i) prevention of ignitions should not be overlooked, given the high level of potential threat to assets in case of escape. The goal of (ii) reintroduce and prescribe fires would be unadvisable

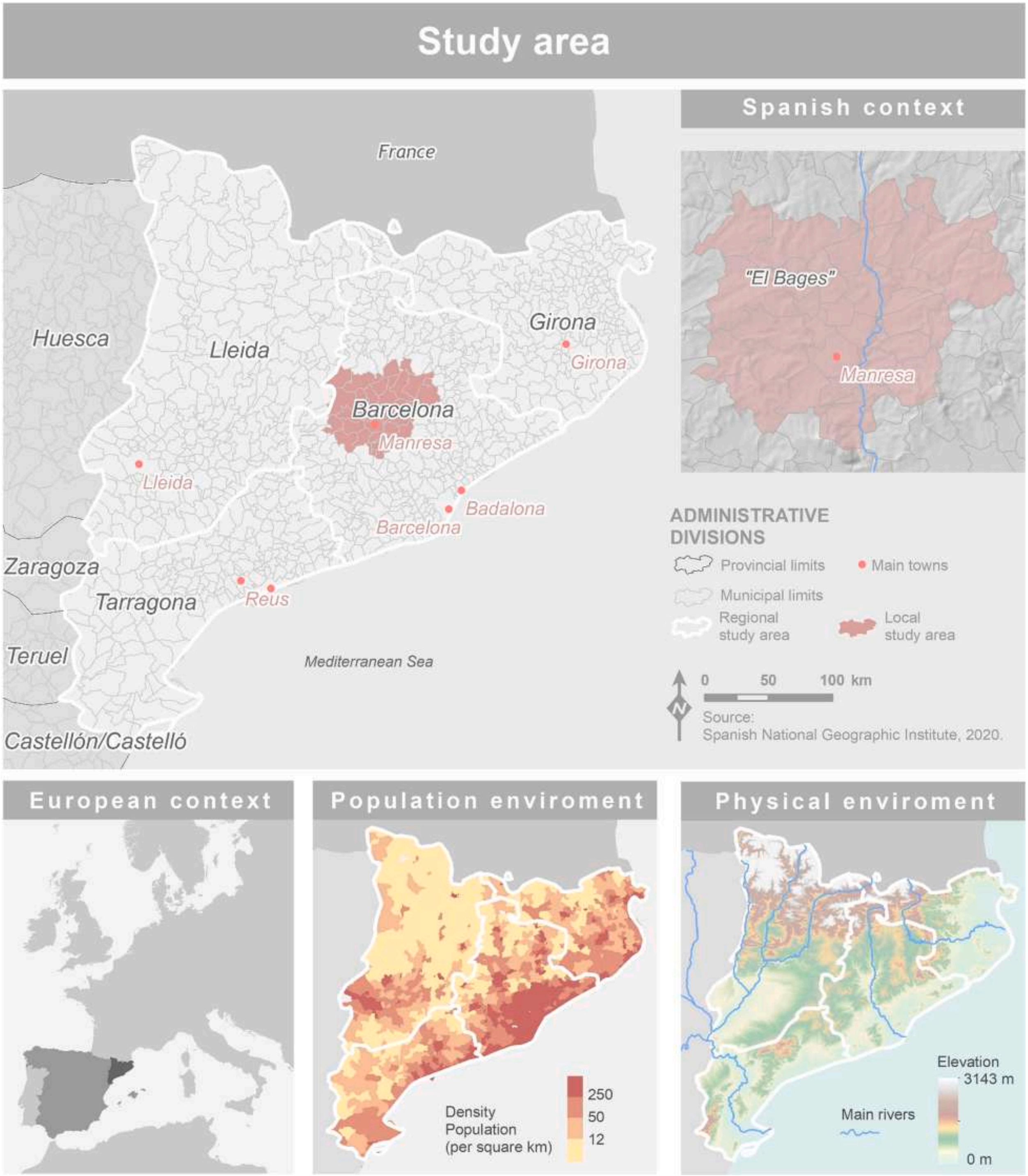

Fig. 2. Location and characteristics of the study area.

given the potential of fires to scape suppression and grow into large fire events, at least until our Mediterranean landscapes are made more resilient by forest and fire management, and land planning. Fire flow paths are critical locations to place fuel treatments (iii) and safe areas (v) in Zone III. Fire-adapted urban and rural planning (iv) should be implemented in the areas potentially impacted by fires originated in the source locations, complemented by a vulnerability analysis.

- **Zone IV: Fire reintroduction.** The extent would encompass areas with low probability of fire occurrence and good prospects for efficient suppression capability and success at IA even though the scenario simulated was extreme (weather at percentile 95th and 10 active fires). This Zone could be considered for goal (i) *prescribed burning and natural or cultural fire reintroduction*, whenever ecological and socioeconomic conditions recommend the establishment of natural or cultural fire regimes. The exposure analysis plays a lesser role in this Zone.

Finally, we zoomed into the local scale to incorporate wildfire behavior simulation into the zoning proposal (step 5.1 and 5.2).

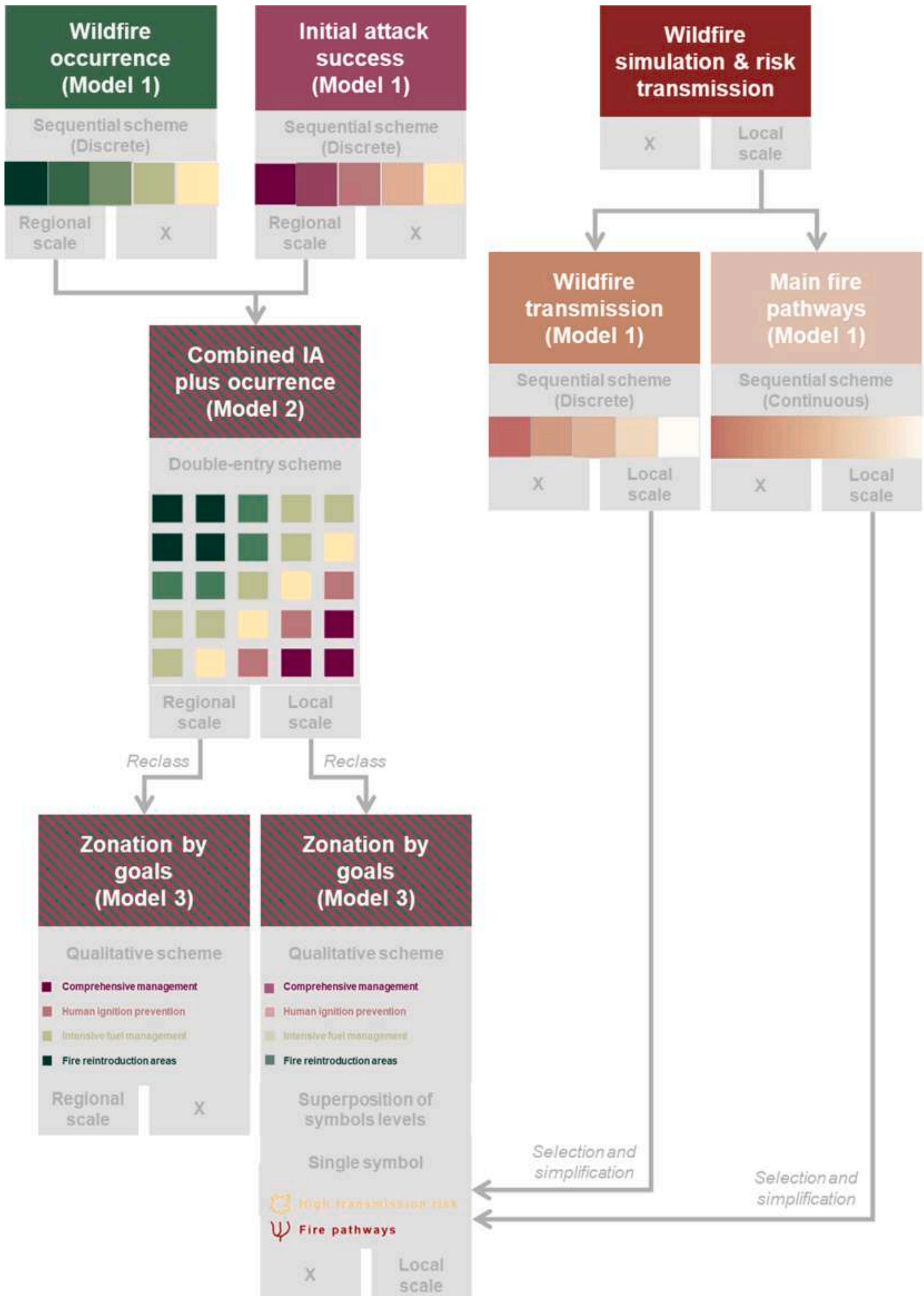

Fig. 3. Methodological scheme for cartographic design and mapping.

2.2. *Study area*

The method was demonstrated in Catalonia (northeastern Spain; Fig. 2), a Mediterranean region with high values at risk and a growing WUI that has experienced extreme fires in the past linked to fuel built-up in the landscape and drought/heat waves (Cardil et al., 2019; Duane and Brotons, 2018; Rodrigues et al., 2020), and faces budgetary challenges related to the general financial situation of the country. Fire occurrence is not generally high, but fire return intervals lower than five years occur in specific locations (Gonzalez-Olabarria et al., 2012). Suppression resources used in the region, up to 2008, were approximately 277.37 (±279.7 sd) firefighters, 33.65 (±32.5 sd) heavy machinery and 10.81 (±7.38 sd) aerial units per each fire over 100 ha (Costafreda-Aumedes et al., 2015). Given the financial situation after the 2008 crisis, no large deviations in resources availability and patterns of use have taken place, and stability is a correct assumption for an analysis of firefighting resources overload.

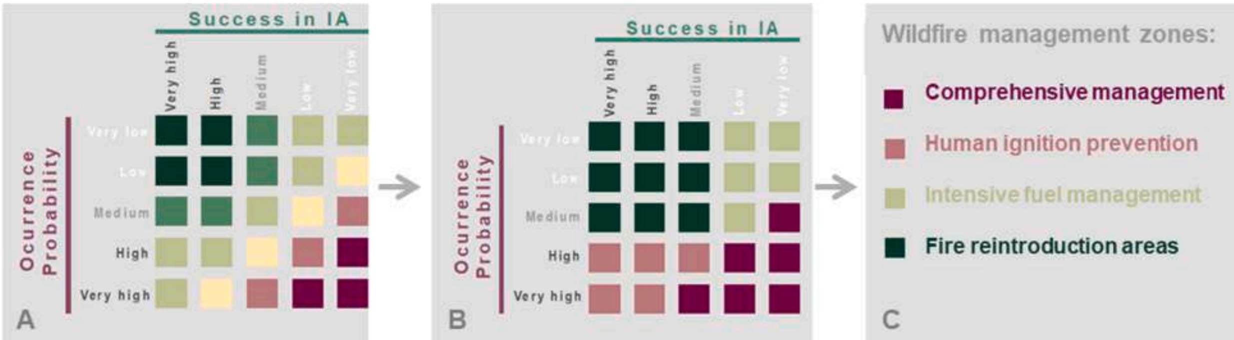

Fig. 4. Double entry legend for the combination and zonation on the basis of fire occurrence and success in IA. A, legend for quantitative combination; B, qualitative legend; and C, description of zoning fire management goals.

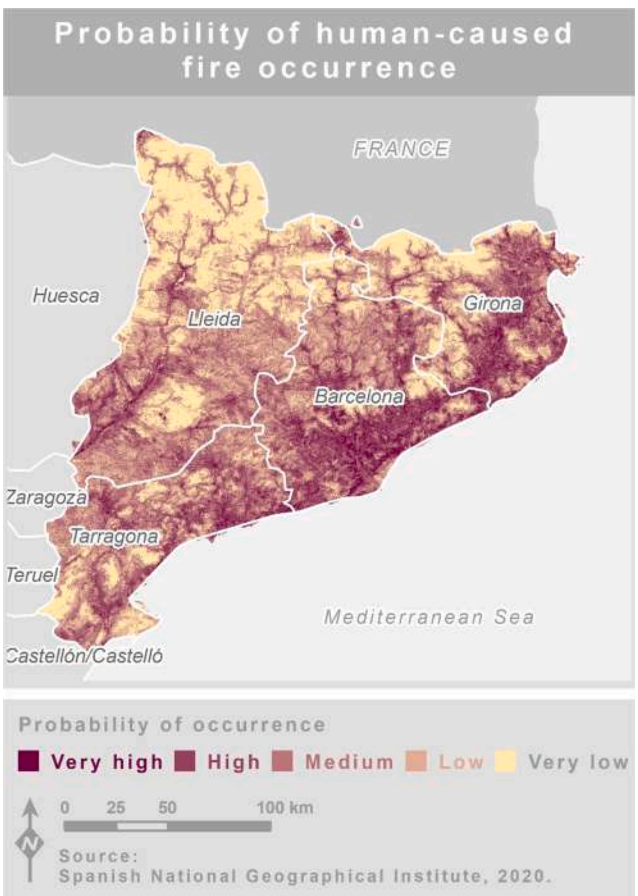

Fig. 5. Spatial distribution of probability of human-caused fire ignition in Catalonia.

2.3. Modelling wildfire occurrence of human-caused fires

Geospatial information about wildfire drivers was used to generate a human-caused fire (HCF) ignition probability raster grid using machine-learning algorithms as proposed by Rodrigues and de la Riva (2014). The method builds upon historical fire records, compiled in the Spanish fire database (EGIF; MAAyMA, 2015), coupled to spatial raster layers (at 40 m resolution) of fire drivers (Costafreda-Aumedes et al., 2017; Leone et al., 2003) depicting accessibility (distance to paved roads, forest tracks and walking trails), human pressure on wildlands (WUI), presence of agricultural activities (Wildland-Agricultural interface, WAI) and sparks from power lines (distance to power lines). The modeling approach relied on Random Forest (RF; Breiman, 2001), a powerful machine learning algorithm very popular in wildfire science due to its high predictive performance (Bar Massada et al., 2012). Binary RF (1-presence versus 0-absence) models were calibrated, trained and tested using the *caret* package (Kuhn, 2008) using the R environment for statistical computing (R Core Team and R Development Team Core, 2017). To do so, a sample of 10,735 fires ignited during the period 1998–2015 was tagged as presence locations and 20 random realizations of pseudo-absence points were built. The performance of the model was evaluated using a k-fold cross validation (k = 10), calculating the area under the Receiver Operating Characteristic curve (AUC; Hanley and McNeil, 1982). The result of this procedure was a raster map describing the spatial pattern of probability of fire occurrence, stationary over the time frame of analysis.

2.4. Modelling success in initial attack

The probability of success in initial attack (IA) was carried out leveraging historical fire data and geospatial information about fire drivers, suppression-related in this case. As described in Rodrigues et al. (2019a), a binary RF model was fitted combining information about the chances at detection of fire events (visibility from roads), arrival time as accessibility to the fire site (distance to paved roads, forest tracks and walking trails), spread potential (temperature, wind speed and fuel type) and demands of suppression resources potentially causing overload (number of active fires in the last 24 h). Again, a binary response variable was built from the EGIF database. In agreement with Plucinski (2012) fires smaller than 10 ha were considered as successfully controlled during the IA stage (presence or success in IA) while fires becoming larger than 50 ha were labeled as escaped fires (absence or failure in IA). The model was calibrated, trained and evaluated using the *caret* package in R environment. Unlike the occurrence likelihood model, which was obtained as a static layer (i.e., stationary over time), success in IA was evaluated investigating two weather and suppression resources scenarios, a baseline ('Base') scenario, with weather at 50th percentile and no simultaneous fires, and a 'Extreme' scenario, with weather at percentile 95th and 10 active fires. Outputs from this methodological step were two raster layers depicting the chances of success in IA. They were compared to analyze IA probability changes due to increased ignitions and hazard. The spatial resolution was set to 40 m as a trade-off solution between computational performance and spatial accuracy. The performance of the model was evaluated as described in section 2.3.

2.5. Wildfire simulation modeling and risk transmission

Failure to prevent ignitions or propagation at the initial stages of a fire through IA leads to exposure of lives and assets, often at considerable distances of the ignition point. Since our focus lied on controlling

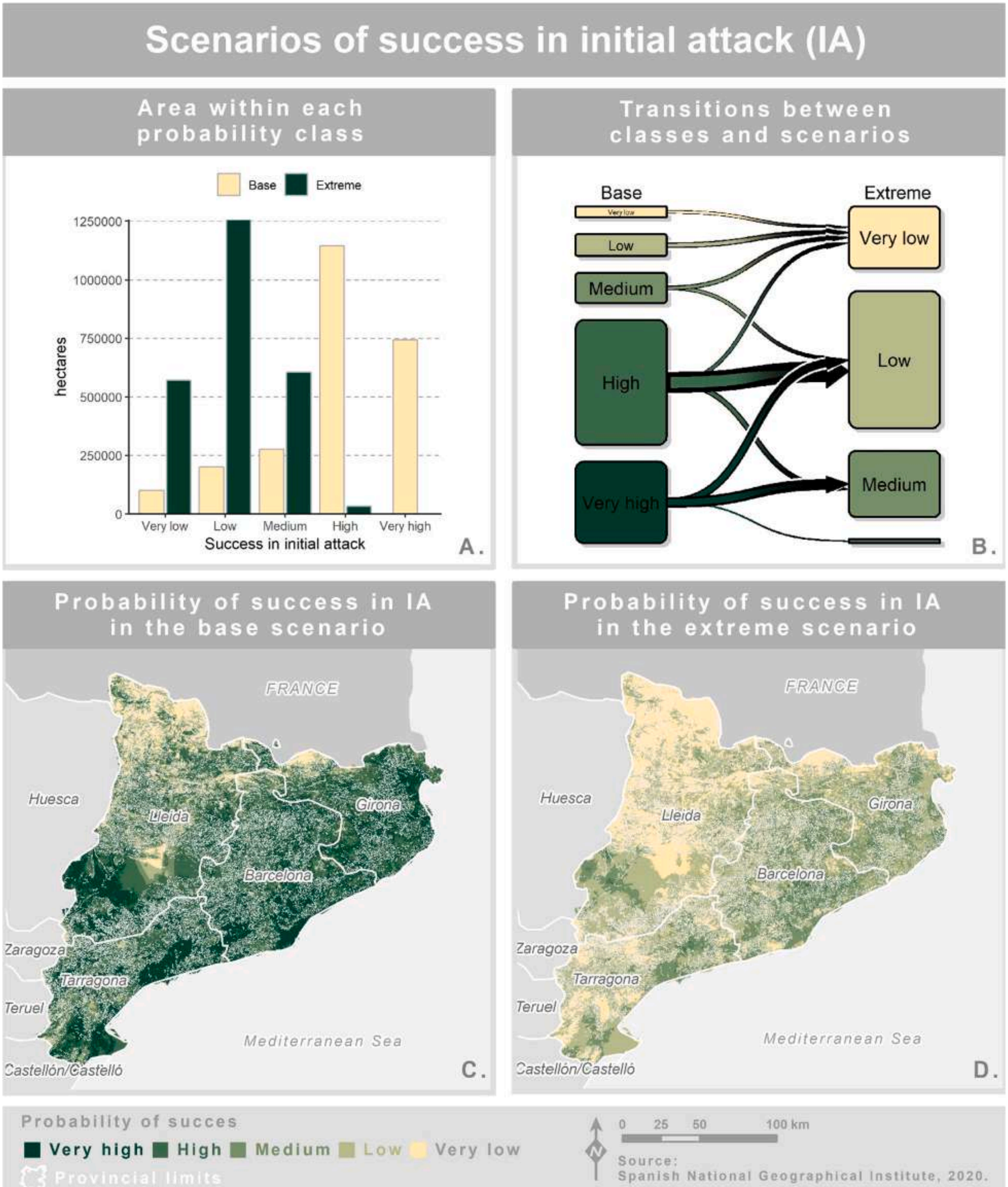

Fig. 6. Summary of scenarios of success in initial attack. A) area within each probability class; B) transitions between classes and scenarios; C) spatial distribution of probability of success in IA in the base scenario; D) spatial distribution of probability of success in IA in the extreme scenario for Catalonia.

the initial stages of highly threatening fire events, these potential impacts needed to be incorporated into decision making and planning from the start, and at the best possible resolution. We set a local scale of analysis and a and higher resolution (40 m) for a pilot area in Catalonia, Bages County, to integrate the transmission analysis as conducted in Alcasena et al (2018a) with our previous regional zonation and goals.

We used the minimum travel time (MTT; Finney, 2002) algorithm as implemented in FlamMap (Finney, 2006) to model fire spread. Fire spread models required information about canopy metrics (canopy cover, base height, bulk density and height), surface fuel types (Scott and Burgan, 2005), topography, fire-weather (fuel moisture content and winds), as well as the spatial pattern of fire occurrence. Hourly weather records from automatic weather stations within the study area were used to characterize the most frequent wind scenario (speed and direction), and derive fuel moisture content (Bradshaw and Borchers, 2000). We simulated 10,000 fire events replicating the historical fire-regime

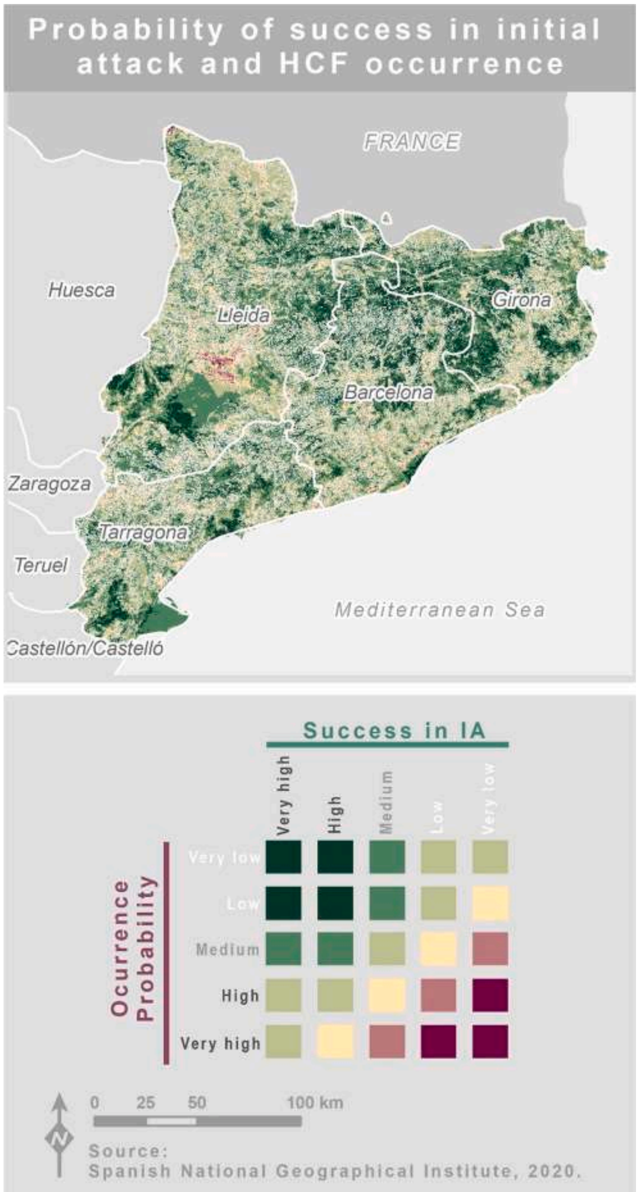

Fig. 7. Spatial distribution of probability of success in initial attack and HCF occurrence. Color indicates an ordered hazard level for the different combinations.

(fire size distribution) under fire prone weather conditions (97th percentile of temperature and wind speed) on the study area ("*Comarca del Bages*") as described in Alcasena et al. (2018a). Fire modeling was conducted at 40 m resolution considering extreme weather conditions (97th percentile) to obtain two outputs: i) counts at each pixel in the study area with the number of buildings potentially burned from fires starting in that location, and ii) the most frequent pathways followed by fires.

Transmission of wildfire to residential housing was addressed using the residential housing footprints in the 1:25,000 scale Spanish national topographic map (BTN25 according to the Spanish acronym; IGN, 2018, 2015) to derive individual structure locations. The BTN25 is the reference cartography used by official institutions such as municipalities to inform landscape and urban planning projects. We generated a centroid point layer from structure polygon (n = 23,440) to accurately locate individual housing units. We overlaid structure centroids and fire perimeters to calculate how many buildings would be affected by our simulated fires, summing the number of exposed buildings from each simulated fire at its ignition pixel. We also derived the most frequent pathways followed by simulated fires. To do so, we calculated the Node Influence Grid, which summarizes the times each pixel fell within a simulated fire pathway (Alcasena et al., 2018a).

2.6. Visualization and mapping

Bridging the fire risk-awareness gap between the scientific community and managers, stakeholders or the general population required specific communication tools condensing spatial information in an efficient and straightforward representation. Cartographic techniques were applied in order to synthesize modeling outcomes and facilitate the transfer of knowledge. In this work we used three different cartographic models (Fig. 3).

Maps in Model 1 were developed using sequential schemes applying different color ramps to differentiate the variables on display. Sequential color schemes are logically arranged from high to low lightness steps (Brewer, 1994) thus, particularly suitable to represent chance or probability. The maps that use this type model are the following:

- Wildfire occurrence (Fig. 5), leveraged a multihued green-to-yellow color ramp. Color value steps from dark green to light yellow depicted high-to-low chances of fire occurrence. This map includes base and extreme scenarios and graphical information which is useful for complete the reading of the map.
- Initial attack success (Fig. 6C and 6D) used a purple-to-yellow ramp; again the color scheme reflects decreasing likelihood.
- Wildfire transmission (Fig. 9A). An interval legend was developed using a red -to- yellow range. In this case, a vector isoline layer was superimposed, highlighting the 60th and 80th percentiles of potentially threatened structures, considered the worst case exposure conditions.
- Main fire pathways (Fig. 9B): continuous legend in the red -to- yellow.

Maps based on Model 2 (Fig. 7 and Fig. 10) utilized a double-entry scheme (Fig. 4A) synthesizing the information from fire occurrence (vertical axis) and success in IA (horizontal axis). In both cases the color scale was graduated in 5 classes from very low to very high. It should be noted that the best situation (top-left corner) corresponded to very low probability of fire occurrence coupled with very high success in the IA, to which dark green color was applied. Conversely, the worst situation was that resulting from a very high probability of occurrence and a very low success in the initial attack (bottom right), to which dark purple color was applied. The hue assign to each corner (green and purple, respectively) were kept along further combinations, so that it is graphically understood it was a cross between the two separate variables what was being represented. These combinations were ordered using a semiological conception of the degree of danger posed by each situation, associating higher danger with a higher load of magenta, a warm color (Pellicer, 1993; Zelanski and Fisher, 2001).

Model 3 was a reworked version of the Model 2 (Fig. 4B and 4C) applying different processes of cartographic generalization. First, we translated the scale of information measurement from a quantitative to a qualitative nature (Fig. 8 and Fig. 11), so it was simplified. The 25 combinations between displayed in Model 2 were reclassified into 4 categories that correspond to WMZs: comprehensive management (Zone I); human ignition prevention (Zone II); intensive fuel management (Zone III) and fire reintroduction areas (Zone IV). Consequently, the type of scheme required was qualitative. When transitioning into the qualitative zoning scheme we kept the ordered perception (Bertin, 1973) of the quantitative version. Hence, we hierarchized the four WMZs according to the need for intervention and the type of actions to be recommended. Model 3 was applied both at a regional and local extent, introducing in the latter the information derived from the wildfire simulation and risk transmission valuation. The inclusion involved two

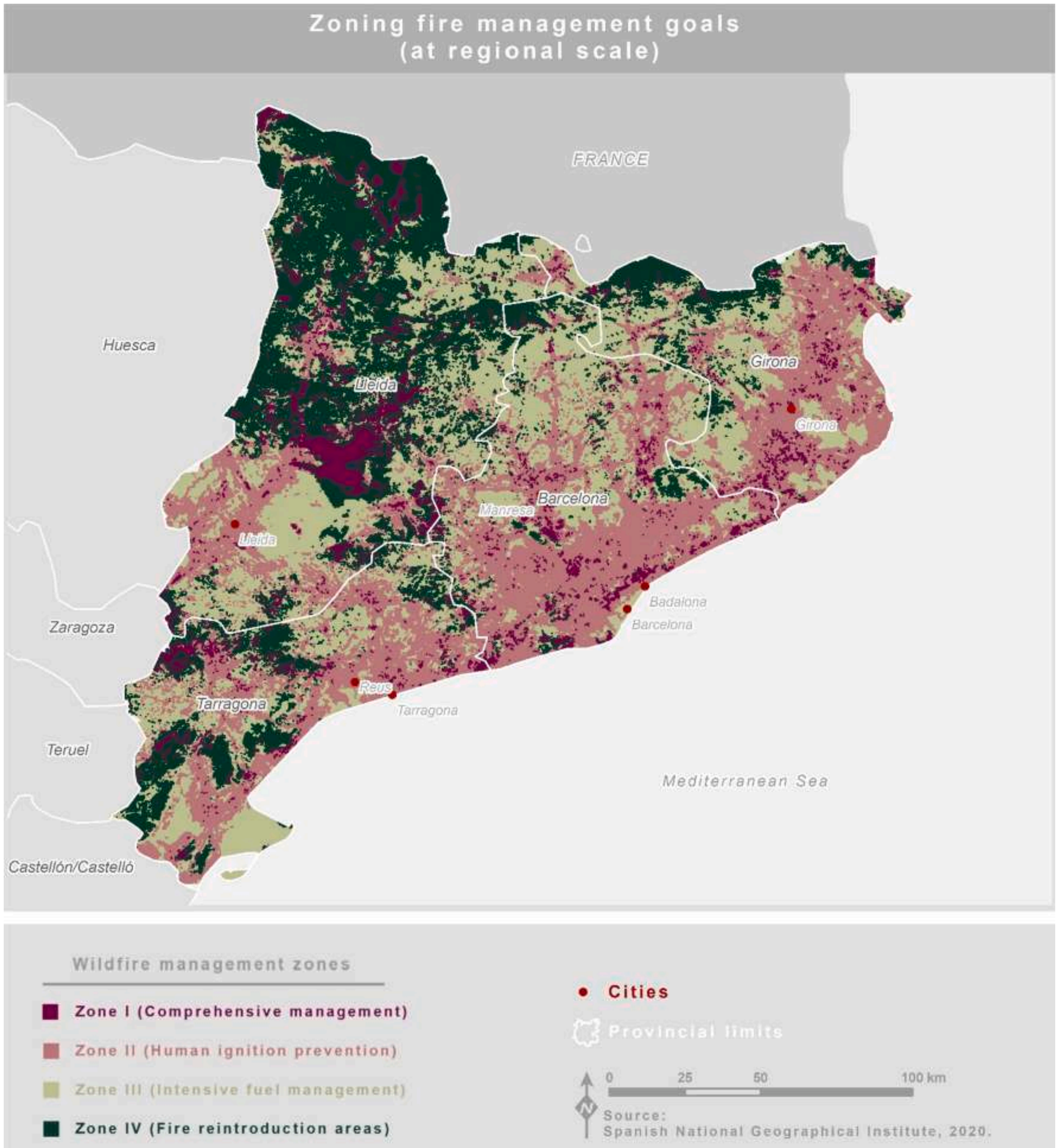

Fig. 8. Regional zonation of Catalonia for combined fire management goals derived from the occurrence probability and IA analysis.

generalization operations (Regnauld and McMaster, 2007): (i) selecting key information related to management goals; and (ii) simplifying the representation, e.g., use single symbols in warm colors (derived from the original legends) so that it is associated properly. In this way we synthesize in a single map the results of the whole methodological process, understanding that was the optimal way to transmit the bulk of information necessary for decision making.

It should also be noted that for models 2 and 3, depending on the regional or local scale, different contextual information is incorporated such as place name, elevation model or urban settlement layer.

3. Results

3.1. Mapping probability of occurrence

Fig. 5 displays the spatial distribution of probability of fire occurrence, highlighting areas in which more ignitions can be expected due to human activities and presence. Accessibility and increased presence of people controlled the chances of a fire starting. Fires were more likely close to urban areas and along the littoral Mediterranean corridor where population densities are higher. Locations with high probability extend towards the hinterland along the main road network. The model attained a good predictive performance with an average AUC value of 0.75 ± 0.03sd.

3.2. Mapping initial attack success

The probability of success in IA described the chances of stopping a fire once started, under two sets of conditions of weather and fire simultaneity. Fig. 6 summarizes the change in probability of success in IA between the ‘Base’ (weather at 50th percentile and no simultaneous fires) and the ‘Extreme’ (weather at percentile 95th and 10 active fires) scenarios. These two contrasting settings depicted mild/regular situations and hazardous weather conditions fostering a fire outbreak, respectively. As can be seen, the change in the predicted probability was vast. Under ‘Base’ circumstances most of the study region was contained

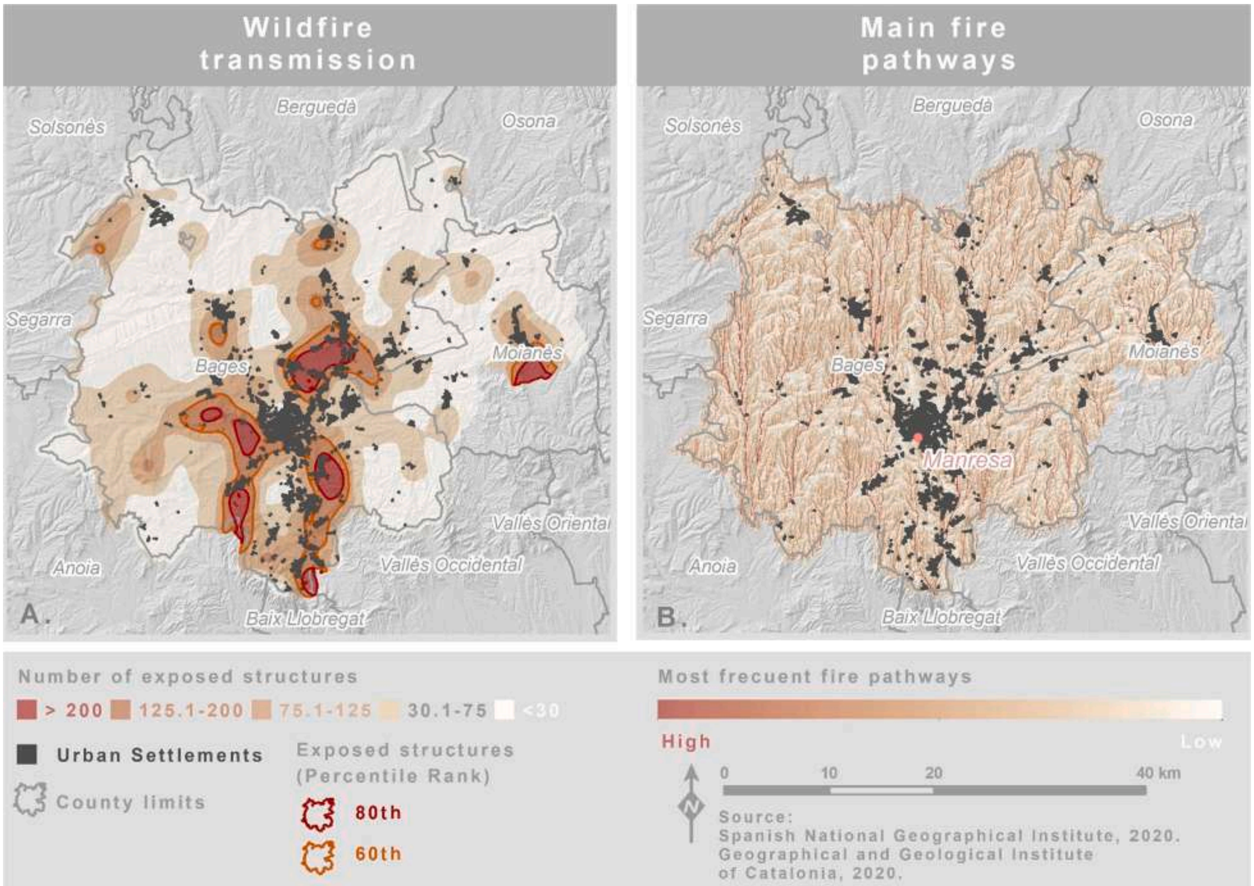

Fig. 9. Spatial distribution of fire behavior simulation outputs in the 'Bages' County. A) transmission risk expressed as number of exposed buildings at pixel level. B) most frequent pathways of fires. We used the wildfire transmission to delineate the community firesheds based on 60th and 80th exposure percentile values.

in the '*High*' to '*Very high*' intervals of chance of success (Fig. 6A and 6C), save from remote enclaves on the central and northwestern end of Pyrenees. However, transitioning towards the 'Extreme' scenario disrupted the chances of controlling a fire before escape. The '*Very high*' interval disappeared (Fig. 6A) and most of the region went from '*Very high*' to '*Medium*' probability or from '*High*' to '*Low*' probability (Fig. 6B), which was the most widespread situation (Fig. 6D). In any case, the most frequent transitional pathways involved a drop of two interval classes ('*Very high*' to '*Medium*' or '*High*' to '*Low*'). Again, the model denoted good predictive performance with an average AUC value of 0.73 ± 0.02.

3.3. Zonation by fire management goals at regional scale: Initial attack vs occurrence probability

The spatial pattern of occurrence likelihood (Fig. 5 above) mirrored, to some extent, the broad pattern of success in IA (Fig. 6C and Fig. 6D). Accessibility controlled the chances of a fire starting; the greater the accessibility the higher the chances of a fire to occur, but also the more likely the success in IA. Nonetheless, the combination of fire occurrence likelihood and the 'Extreme' scenario of success in IA revealed some interesting situations. Fig. 7 displays their combined spatial footprint using a double-entry legend. The rationale behind this scheme was that spatial coincidence of high occurrence and low capability of controlling fires set up the most hazardous combinations and vice versa. In between we found an array of mid-range combinations. For example, along the coast, where we found greater containment capacity due to the greater presence of densely populated areas, we detected intermediate hazard situations (level 3–4). In the same way, areas around the Pyrenees, despite their lower rate of occurrence, could lead to dangerous situations due to isolation and reduced IA capability. However, the pre-Pyrenean area in the center of the province of Lleida stands out, with the highest hazard values.

The double-entry scheme from Fig. 7 was translated into a priority-management-goal zoning scheme as described in section 2.2.1. Fig. 8 displays the spatial distribution of the proposed zoning scheme. The spatial footprint of Zone I was noticeably in the northeastern end and several small enclaves close the coast. Zone II occupies a large portion the coastal zone, surrounding Zone I, running into the hinterlands along the road network. Zone III covers a vast region over the hinterlands, characterized by large extensions of forest lands, mid-tier population density and limited accessibility. The major cluster of Zone IV extended mostly over the northwest and north. A second large spot was identified in the southern end as well as some sparse enclaves close the coast.

3.4. Mapping community firesheds and fire pathways

Zooming into the local scale in the Bages County, the simulation modelling allowed to determine critical outputs related to exposure consequences of escaped fires, which were then used to inform about the best locations for fire management interventions to be applied before or at the first stages of fires. Fig. 9A shows the locations of inhabited areas in Bages County, and their relative position with regard to areas that emitted fires potentially affecting increasing fractions of buildings, up to a maximum number of 138. As expected, the neighboring areas of towns and cities were the zones with the highest potential to threaten residential buildings, though the closest locations were not necessarily the ones affecting the largest amount of buildings. Fig. 9B displays the most frequent pathways followed by fires, linking the ignition point with the farthest edge of each perimeter shape out of the 10,000 fires that were

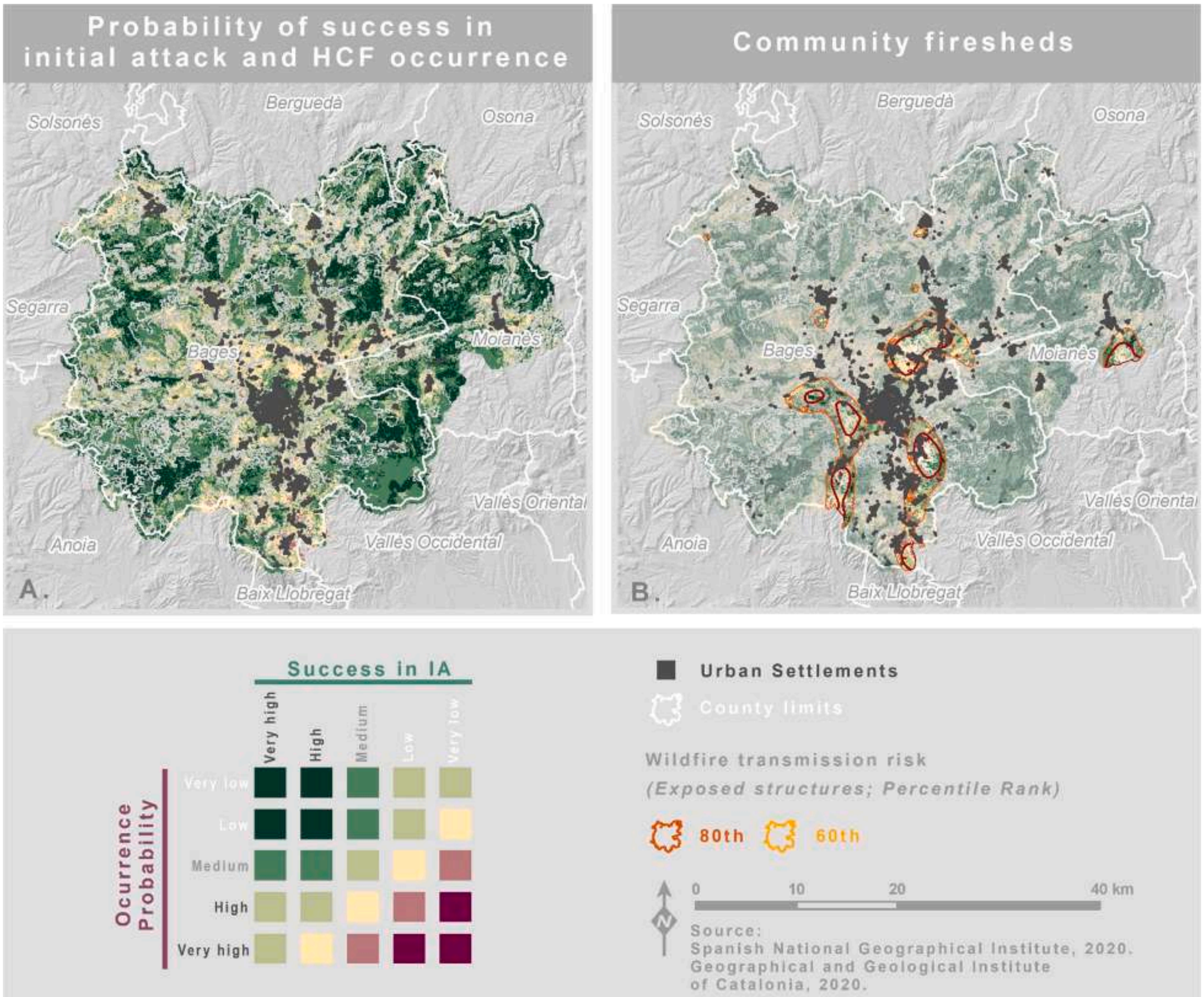

Fig. 10. High-resolution mapping of transmission risk (number of buildings exposed to high intensity fires), success in IA and occurrence probability.

modelled. As can be observed, several main pathways could be identified; most frequent trajectories followed a North-South direction, governed by the predominant local wind regime.

3.5. *Zonation by management goals at local scale: Integrating management zones with local risk transmission*

While transmission outputs alone (Fig. 9) already provided useful information to set a solid basis for decision support, combining them with the joint probability of fire occurrence and success in IA 'completed' the picture towards an enhanced representation of likelihood plus exposure mediated by IA. Fig. 10 replicated the mapped outputs from section 3.4 combined with the zonation scheme developed in 3.3. This figure allowed focusing on the most critical fire-source locations potentially affecting a large fraction of the housing environment. To do so, we highlighted the subset corresponding to the two top intervals (percentiles 60 and 80) in terms of affected buildings (Fig. 10B). Similarly, we were able to identify the trajectories more frequently followed by fires (Fig. 9B). These source and path locations may serve to guide the process of urban sprawl (introducing fire-smart actions in the urban planning agenda, or forcing fire-smart designs and safe fuel buffers), or target priority areas for fuel treatments, or other management goals depending on Zone guidance, which provide a frame for prioritizing actions. Fig. 11 compiles the aforementioned outputs into a specific cartographic product to guide decision making at local scale for our pilot area.

4. Discussion

The road towards resilient landscapes, fire-adapted communities and safe suppression must be paved with expert criteria and science-based decision-making tools (Dunn et al., 2020). In this work we provide a comprehensive zoning scheme by combining wildfire modelling outputs into management zones. We focused on actions to be taken before or during the first stages of any fire, in line with traditional policies in firefighting and civil protection organizations all over the world (i.e. arrival times shorter than one hour, arrival before a fire reached certain size; Plucinski 2019, 2012). In agreement with the risk assessment scheme most used in wildfire science (Scott et al., 2013) and in line with a cohesive management strategy (USDA Forest Service, 2014), we focused on likelihood at the regional level, and then exposure at the local scale. For example, forest prevention plans often require information at regional scales, covering vast areas, whereas evacuation planning after determining the number and kind of exposed assets demands local high-resolution outputs (Cirella et al., 2014). Recently, efforts are being devoted to incorporate suppression capabilities into the equation to provide a full spectrum coverage of the 'fire cycle' while enhancing operational decision making, resource and treatment allocation optimization, among other management goals (Castellnou et al., 2019; Gonzalez-Olabarria et al., 2019; Rodríguez y Silva et al., 2014;

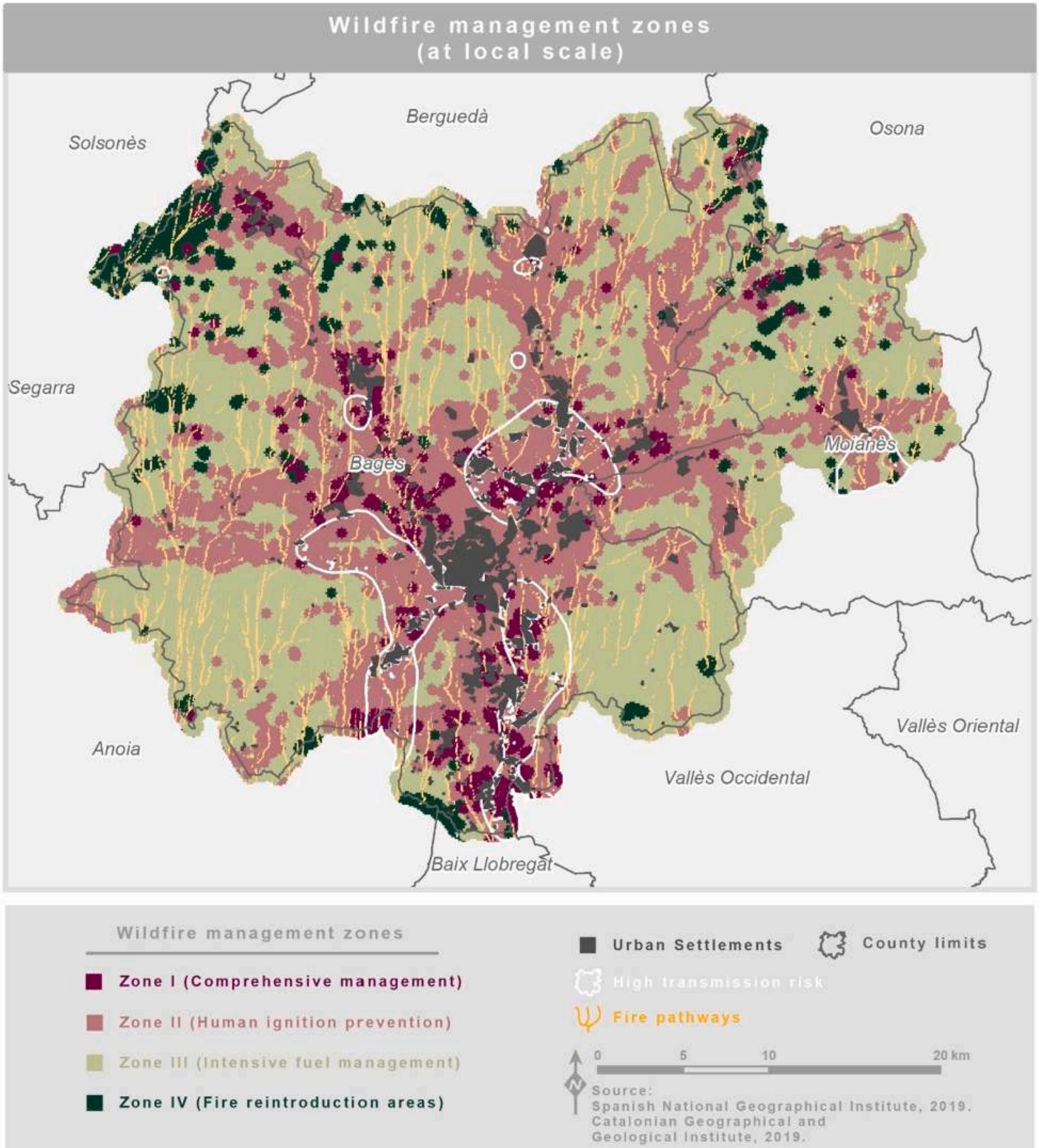

Fig. 11. Spatial distribution of zones for fire management at the local scale.

Wei et al., 2019, 2018). Approaches such as ours add to the ongoing trend by promoting science-based decision-making while providing tools for engaging stakeholders towards more inclusive policies (Gonzalez-Mathiesen et al., 2021). Compared to the most recent and detailed strategic spatial schemes in the region, such as the analysis by municipality in Alcasena et al. (2019), our approach allows for more integrated information in terms of objectives and priorities. Instead of separate maps addressing each goal, we prioritized and spatially located joint fire management goals in intervention zones. Likewise, augmenting the spatial resolution of analysis unveils local patterns –that would otherwise remain hidden– while transcending administrative boundaries (i.e., municipality to pixel level), thus facilitating cohesive strategies and shared efforts. To facilitate outreach and risk communication we leveraged mapping and cartographic techniques to integrate risk components into meaningful and straightforward outputs (Cao et al., 2016). Risk communication is a challenging endeavor due to the confluence of different perceptions from different actors (e.g., managers, scientists or the general public). In this sense, the workflow provided here may be easily adapted to fit other specific management goals (i.e. prepositioning or placing permanent suppression resources) or policies (i.e. land management strategies).

Our management recommendations were based on a diagnosis that focused on the pre-fire or initial stages in the development of large or extreme fires (ignition likelihood plus success in the IA), the most damaging events and the ones that pose the biggest challenge to land managers and civil protection agencies (Castellnou et al., 2019). The cartographic product ignition probability combined with fire escape probability from IA (Fig. 7) highlighted critical situations that could not be identified otherwise, allowing a zonation at the regional scale (Fig. 8) for optimal allocation of our stated goals: (i) prevent ignitions threating assets, (ii) reintroduce and prescribe fires, (iii) optimize fuel treatment allocation, (iv) provide guidance towards fire-adapted urban and rural planning and (v) facilitate safe suppression conditions. Analyses and outputs targeted very hazardous fire-prone weather conditions (i.e., dry and warm) aiming at be prepared for the worst possible circumstances. The *'extreme'* scenario mimics an extraordinary heatwave episode with very strong winds. A recent example of this kind of situation was found in the '*Torre del Español*' fire event (Tarragona, southeast of Catalonia). The fire took place on June 2019 during a severe drought episode coupled to strong winds, ignited by self-combustion of fermented manure in a local farm. It burned over 6,500 ha, being eventually controlled by firefighting services only after wind stopped blowing. 350 firefighters and 260 members of the Military Emergency Unit (UME) participated in the extinction tasks. Similar conditions were found in '*La Jonquera*' fire in July 2012 (Girona, northeast of Catalonia), burning more than 13,000 ha driven by strong northerly winds. Leaving aside injuries and the large amount of resources deployed, the effects of the fire were noticeable from hundreds of kilometers afar, carrying particulate matter in suspension up to the metropolitan area of Barcelona. According to climate projections, heatwaves and drought episodes like these are expected to occur more frequently in the future, thus the region is likely to endure similar fires again (Calheiros et al., 2021; Raftery et al., 2017).

The proposed zonation scheme is in line with the newest paradigms that advocate for proactive strategies to mitigate fire risk (Castellnou et al., 2019; Moreira et al., 2020). Adopting this new management archetypes poses multiple challenges that had to do with its implementation, shared responsibilities and lines of action to follow, among others (Wunder et al., 2021). But, uncertainties aside, there is a growing consensus about the need for engaging scientists and stakeholders to develop and guide sound plans. For instance, the '*let it burn*' initiative that focuses on reintroducing fires in the landscape or the development of prescribed burning plans are gaining considerable attention in Europe. However, their efficiency and adequacy depends on their proper design, not only on the 'how' but the 'when' and the 'where', to which our approach can certainly contribute (Duane et al., 2019). For instance, Zones III and IV outline candidate areas for preventive burnings at the regional scale (Fig. 8), which can be further refined at the local level allocating specific plans to break fuel continuity over dominant firepaths (Fig. 11) or promoting agricultural mosaics as a tool for landscape fragmentation (Aquilué et al., 2020).

Analyses at the local scale allowed accounting for landscape level information about fire impacts and behavior in the long run, central to design adaptation trajectories towards increased policy integration. Including such inputs into the equation enhances decision making at this particular scale (Gonzalez-Mathiesen et al., 2021). In this sense, we deliberately besieged urban planning, since it involves both land management and prognosis to guide the process of urban sprawl, thus, potentially benefiting from fire risk-related recommendations towards a safer and more efficient planning strategy. This is particularly important to implement sound policies to adapt urban and rural communities highly exposed to wildfires as those intermingling in the WUI (Darques, 2015). Such locations fall mostly within the *comprehensive management zone* (Zone I), which denotes hazardous regions in which a variety of mitigation measures should be put in place to reduce exposure (Alcasena et al., 2015) or reduce fire ignitions that may ultimately reach human communities (Ager et al., 2017). In fact, Zone I is among the few opportunities to insist on the total fire exclusion policy and keep the 'prevention plus suppression' approach aimed at precluding fires from igniting or controlling them as soon as possible (Gonzalez-Olabarria et al., 2019; González-Olabarria et al., 2015). Notwithstanding, this approach must be strengthened by fostering community resilience, for instance, implementing building and construction codes (Pastor et al., 2020; Syphard et al., 2017) or managing fuel continuity in the WUI and its vicinity (Calviño-Cancela et al., 2016).

5. Summary and conclusions

In this work we demonstrate how mapping science can contribute to integrate scientific knowledge into managerial recommendations. Our proposal combines and translates complex models and outputs (e.g., probabilistic representations of fire ignition or spread simulation) in a comprehensive but straightforward zoning scheme that:

- Supports management decisions at multiple scales, from regional zoning to highly detailed local plans.
- Identifies priority intervention areas that require immediate action, particularly those in fire-prone WUI zones.
- Allocates zones were the current fire exclusion policy may be still imperative.
- We believe our approach to be particularly suitable to:
- Promote risk awareness in non-specialized audiences.
- Guide ongoing fuel reduction programs.
- Design innovative strategies towards fire-adapted communities and landscapes.

CRediT authorship contribution statement

Marcos Rodrigues: Conceptualization, Methodology, Investigation, Writing – original draft, Writing – review & editing. **María Zúñiga-Antón:** Visualization, Investigation, Writing – original draft. **Fermín Alcasena:** Conceptualization, Writing – review & editing. **Pere Gelabert:** Data curation, Writing – original draft. **Cristina Vega-Garcia:** 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.

Acknowledgements

This work has been financed by the Spanish Ministry of Economy and Competitiveness, postdoctoral '*Juan de la Cierva Formación'* research grant (FJCI-2016-31090) awarded by Marcos Rodrigues. The work was partially funded by the projects FirEUrisk "DEVELOPING A HOLISTIC, RISK-WISE STRATEGY FOR EUROPEAN WILDFIRE MANAGEMENT". This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 101003890; and CLIMARK "Forest management promotion for climate mitigation through the design of a local market of climatic credits" (LIFE16 CCM/ES/000065).

References

Ager, A.A., Day, M.A., Alcasena, F.J., Evers, C.R., Short, K.C., Grenfell, I., 2021. Predicting Paradise: Modeling future wildfire disasters in the western US. Sci. Total Environ. 784, 147057. https://doi.org/10.1016/j.scitotenv.2021.147057.

Ager, A.A., Day, M.A., Palaiologou, P., Houtman, R.M., Ringo, C., Evers, C.R., 2019. Cross-boundary wildfire and community exposure: A framework and application in the western u.s. USDA For. Serv. - Gen. Tech. Rep. RMRS-GTR 2019, ii–34.

Ager, A.A., Evers, C.R., Day, M.A., Preisler, H.K., Barros, A.M.G., Nielsen-Pincus, M., Zia, A., 2017. Network analysis of wildfire transmission and implications for risk governance. PLoS One 12 (3), e0172867. https://doi.org/10.1371/journal.pone.0172867.

Alcasena, F.J., Ager, A.A., Bailey, J.D., Pineda, N., Vega-García, C., 2019. Towards a comprehensive wildfire management strategy for Mediterranean areas: Framework development and implementation in Catalonia. Spain. J. Environ. Manage. 231, 303–320. https://doi.org/10.1016/j.jenvman.2018.10.027.

Alcasena, F.J., Ager, A.A., Salis, M., Day, M.A., Vega-Garcia, C., 2018a. Wildfire spread, hazard and exposure metric raster grids for central Catalonia. Data Br. 17, 1–5. https://doi.org/10.1016/j.dib.2017.12.069.

Alcasena, F.J., Evers, C.R., Vega-Garcia, C., 2018b. The wildland-urban interface raster dataset of Catalonia. Data Br. 17, 124–128. https://doi.org/10.1016/j.dib.2017.12.066.

Alcasena, F.J., Salis, M., Ager, A.A., Arca, B., Molina, D., Spano, D., 2015. Assessing Landscape Scale Wildfire Exposure for Highly Valued Resources in a Mediterranean Area. Environ. Manage. 55 (5), 1200–1216. https://doi.org/10.1007/s00267-015-0448-6.

Aquilué, N., Fortin, M.-J., Messier, C., Brotons, L., 2020. The Potential of Agricultural Conversion to Shape Forest Fire Regimes in Mediterranean Landscapes. Ecosystems 23 (1), 34–51. https://doi.org/10.1007/s10021-019-00385-7.

Bar Massada, A., Syphard, A.D., Stewart, S.I., Radeloff, V.C., 2012. Wildfire ignition-distribution modelling: a comparative study in the Huron-Manistee National Forest, Michigan, USA. Int. J. Wildl. Fire 22, 174–183. https://doi.org/10.1071/WF11178.

Benali, A., Sá, A.C.L., Pinho, J., Fernandes, P.M., Pereira, J.M.C., 2021. Understanding the Impact of Different Landscape-Level Fuel Management Strategies on Wildfire Hazard in Central Portugal. Forests 12 (5), 522. https://doi.org/10.3390/f12050522.

Bertin, J., 1973. Sémiologie graphique: Les diagrammes-Les réseaux-Les cartes.

Bowman, D.M.J.S., Balch, J., Artaxo, P., Bond, W.J., Cochrane, M.A., D'Antonio, C.M., DeFries, R., Johnston, F.H., Keeley, J.E., Krawchuk, M.A., Kull, C.A., Mack, M., Moritz, M.A., Pyne, S., Roos, C.I., Scott, A.C., Sodhi, N.S., Swetnam, T.W., 2011. The human dimension of fire regimes on Earth. J. Biogeogr. 38, 2223–2236. https://doi.org/10.1111/j.1365-2699.2011.02595.x.

Bowman, D.M.J.S., Balch, J.K., Artaxo, P., Bond, W.J., Carlson, J.M., Cochrane, M.A., D'Antonio, C.M., DeFries, R.S., Doyle, J.C., Harrison, S.P., Johnston, F.H., Keeley, J.E., Krawchuk, M.A., Kull, C.A., Marston, J.B., Moritz, M.A., Prentice, I.C., Roos, C.I., Scott, A.C., Swetnam, T.W., van der Werf, G.R., Pyne, S.J., 2009. Fire in the Earth system. Science 324 (5926), 481–484. https://doi.org/10.1126/science:1163886.

Bradshaw, G.A., Borchers, J.G., 2000. Uncertainty as information: narrowing the science-policy gap. Conserv. Ecol. 4, 7.

Breiman, L., 2001. Random forests. Mach Learn 45, 5–32.

Brewer, C., 1994. Color Use Guidelines for Mapping and Visualization. In: MacEachren, A.M., Taylor, D.R. (Eds.), Visualization in Modern Cartography. Elsevier Science, Tarrytown, NY, pp. 123–147.

Calheiros, T., Pereira, M.G., Nunes, J.P., 2021. Assessing impacts of future climate change on extreme fire weather and pyro-regions in Iberian {Peninsula}. Sci. Total Environ. 754, 142233. https://doi.org/10.1016/j.scitotenv.2020.142233.

Calviño-Cancela, M., Chas-Amil, M.L., García-Martínez, E.D., Touza, J., 2016. Wildfire risk associated with different vegetation types within and outside wildland-urban interfaces. For. Ecol. Manage. 372, 1–9. https://doi.org/10.1016/j.foreco.2016.04.002.

Camarero, J.J., Sangüesa-Barreda, G., Pérez-Díaz, S., Montiel-Molina, C., Seijo, F., López-Sáez, J.A., 2019. Abrupt regime shifts in post-fire resilience of Mediterranean mountain pinewoods are fuelled by land use. Int. J. Wildl. Fire 28 (5), 329. https://doi.org/10.1071/WF18160.

Cao, Y., Boruff, B.J., McNeill, I.M., 2016. Is a picture worth a thousand words? Evaluating the effectiveness of maps for delivering wildfire warning information. Int. J. Disaster Risk Reduct. 19, 179–196. https://doi.org/10.1016/j.ijdrr.2016.08.012.

Cardil, A., Vega-García, C., Ascoli, D., Molina-Terrén, D.M., Silva, C.A., Rodrigues, M., 2019. How does drought impact burned area in Mediterranean vegetation communities? Sci. Total Environ. 693, 133603. https://doi.org/10.1016/j.scitotenv.2019.133603.

Castellnou, M., Prat-Guitart, N., Arilla, E., Larrañaga, A., Nebot, E., Castellarnau, X., Vendrell, J., Pallàs, J., Herrera, J., Monturiol, M., Cespedes, J., Pagès, J., Gallardo, C., Miralles, M., 2019. Empowering strategic decision-making for wildfire management: avoiding the fear trap and creating a resilient landscape. Fire Ecol. 15, 31. https://doi.org/10.1186/s42408-019-0048-6.

Cervera, T., Pino, J., Marull, J., Padró, R., Tello, E., 2019. Understanding the long-term dynamics of forest transition: From deforestation to afforestation in a Mediterranean landscape (Catalonia, 1868–2005). Land use policy 80, 318–331. https://doi.org/10.1016/j.landusepol.2016.10.006.

Cirella, G., Semenzin, E., Critto, A., Marcomini, A., 2014. Natural Hazard Risk Assessment and Management Methodologies Review: Europe. pp. 329–358. Doi: 10.1007/978-94-007-7161-1_16.

Costafreda-Aumedes, S., Cardil, A., Molina, D., Daniel, S., Mavsar, R., Vega-Garcia, C., 2015. Analysis of factors influencing deployment of fire suppression resources in Spain using artificial neural networks. iForest -. Biogeosciences For. 008, e1–e8. https://doi.org/10.3832/ifor1329-008.

Costafreda-Aumedes, S., Comas, C., Vega-Garcia, C., 2017. Human-caused fire occurrence modelling in perspective: a review. Int. J. Wildl. Fire 26 (12), 983. https://doi.org/10.1071/WF17026.

Coughlan, M.R., 2015. Traditional fire-use, landscape transition, and the legacies of social theory past. Ambio 44 (8), 705–717. https://doi.org/10.1007/s13280-015-0643-y.

Curt, T., Frejaville, T., 2018. Wildfire Policy in Mediterranean France: How Far is it Efficient and Sustainable? Risk Anal. 38 (3), 472–488. https://doi.org/10.1111/risa:2018.38.issue-310.1111/risa:12855.

Darques, R., 2015. Mediterranean cities under fire. A critical approach to the wildland–urban interface. Appl. Geogr. 59, 10–21. https://doi.org/10.1016/j.apgeog.2015.02.008.

Doerr, S.H., Santín, C., 2016. Global trends in wildfire and its impacts: perceptions versus realities in a changing world. Philos. Trans. R. Soc. B Biol. Sci. 371 (1696), 20150345. https://doi.org/10.1098/rstb.2015.0345.

Duane, A., Aquilué, N., Canelles, Q., Morán-Ordoñez, A., De Cáceres, M., Brotons, L., 2019. Adapting prescribed burns to future climate change in Mediterranean landscapes. Sci. Total Environ. 677, 68–83. https://doi.org/10.1016/j.scitotenv.2019.04.348.

Duane, A., Brotons, L., 2018. Synoptic weather conditions and changing fire regimes in a Mediterranean environment. Agric. For. Meteorol. 253–254, 190–202. https://doi.org/10.1016/j.agrformet.2018.02.014.

Dunn, C.J., O'Connor, C.D., Abrams, J., Thompson, M.P., Calkin, D.E., Johnston, J.D., Stratton, R., Gilbertson-Day, J., 2020. Wildfire risk science facilitates adaptation of fire-prone social-ecological systems to the new fire reality. Environ. Res. Lett. 15 (2), 025001. https://doi.org/10.1088/1748-9326/ab6498.

Dupuy, J.-L., Fargeon, H., Martin-StPaul, N., Pimont, F., Ruffault, J., Guijarro, M., Hernando, C., Madrigal, J., Fernandes, P., 2020. Climate change impact on future wildfire danger and activity in southern Europe: a review. Ann. For. Sci. 77 (2) https://doi.org/10.1007/s13595-020-00933-5.

Espinosa, J., Palheiro, P., Loureiro, C., Ascoli, D., Esposito, A., Fernandes, P.M., 2019. Fire-severity mitigation by prescribed burning assessed from fire-treatment encounters in maritime pine stands. Can. J. For. Res. 49 (2), 205–211. https://doi.org/10.1139/cjfr-2018-0263.

Fernandes, P.M., 2013. Landscape and Urban Planning Fire-smart management of forest landscapes in the Mediterranean basin under global change 110, 175–182.

Fernandes, P.M., Pacheco, A.P., Almeida, R., Claro, J., 2016. The role of fire-suppression force in limiting the spread of extremely large forest fires in Portugal. Eur. J. For. Res. 135 (2), 253–262. https://doi.org/10.1007/s10342-015-0933-8.

Finney, M.A., 2006. An overview of FlamMap fire modeling capabilities. In: Fuels Management—how to Measure Success. Department of Agriculture, Forest Service, Rocky Mountain Research Station, Portland, pp. 28–30.

Finney, M.A., 2002. Fire growth using minimum travel time methods. Can. J. For. Res. 32 (8), 1420–1424. https://doi.org/10.1139/x02-068.

Finney, M.A., McHugh, C.W., Grenfell, I.C., Riley, K.L., Short, K.C., 2011. A simulation of probabilistic wildfire risk components for the continental United States.

Fox, D.M., Martin, N., Carrega, P., Andrieu, J., Adnès, C., Emsellem, K., Ganga, O., Moebius, F., Tortorollo, N., Fox, E.A., 2015. Increases in fire risk due to warmer summer temperatures and wildland urban interface changes do not necessarily lead to more fires. Appl. Geogr. 56, 1–12. https://doi.org/10.1016/J.APGEOG.2014.10.001.

Galizia, L.F.d.C., Rodrigues, M., 2019. Modeling the Influence of Eucalypt Plantation on Wildfire Occurrence in the Brazilian Savanna Biome. Forests 10 (10), 844. https://doi.org/10.3390/f10100844.

Gonzalez-Mathiesen, C., Ruane, S., March, A., 2021. Integrating wildfire risk management and spatial planning – A historical review of two Australian planning systems. Int. J. Disaster Risk Reduct. 53, 101984. https://doi.org/10.1016/j.ijdrr.2020.101984.

Gonzalez-Olabarria, J.R., Brotons, L., Gritten, D., Tudela, A., Teres, J.A., 2012. Identifying location and causality of fire ignition hotspots in a Mediterranean region. Int. J. Wildl. Fire 21 (7), 905. https://doi.org/10.1071/WF11039.

González-Olabarria, J.R., Mola-Yudego, B., Coll, L., 2015. Different Factors for Different Causes: Analysis of the Spatial Aggregations of Fire Ignitions in Catalonia (Spain). Risk Anal. 35 (7), 1197–1209. https://doi.org/10.1111/risa:2015.35.issue-710.1111/risa:12339.

Gonzalez-Olabarria, J.R., Reynolds, K.M., Larrañaga, A., Garcia-Gonzalo, J., Busquets, E., Pique, M., 2019. Strategic and tactical planning to improve suppression efforts against large forest fires in the Catalonia region of Spain. For. Ecol. Manage. 432, 612–622. https://doi.org/10.1016/j.foreco.2018.09.039.

Hanley, J.A., McNeil, B.J., 1982. The meaning and use of the area under a receiver operating characteristic (ROC) curve. Radiology 143 (1), 29–36.

IGN, 2018. Mapas vectoriales y bases cartográficas y topográficas a escala 1:25,000 para explotación y consulta mediante sistemas de información geográfica.

IGN, 2015. MDT25.

Krawchuk, M.A., Moritz, M.A., Parisien, M.-A., Van Dorn, J., Hayhoe, K., Chave, J., 2009. Global pyrogeography: the current and future distribution of wildfire. PLoS One 4 (4), e5102. https://doi.org/10.1371/journal.pone.0005102.

Kuhn, M., 2008. Building Predictive Models in R Using the caret Package. J. Stat. Software, Artic. 28, 1–26. https://doi.org/10.18637/jss.v028.i05.

Lasanta, T., Khorchani, M., Pérez-Cabello, F., Errea, P., Sáenz-Blanco, R., Nadal-Romero, E., 2018. Clearing shrubland and extensive livestock farming: Active prevention to control wildfires in the Mediterranean mountains. J. Environ. Manage. 227, 256–266. https://doi.org/10.1016/j.jenvman.2018.08.104.

Leone, V., Koutsias, N., Martínez, J., 2003. The human factor in fire danger assessment, in: Chuvieco, E. (Ed.), Wildland Fire Danger Estimation and Mapping. The Role of Remote Sensing Data. World Scientific Publishing, Singapore.

MAAyMA, 2015. Estadística General de Incendios Forestales. Madrid.

Modugno, S., Balzter, H., Cole, B., Borrelli, P., 2016. Mapping regional patterns of large forest fires in Wildland-Urban Interface areas in Europe. J. Environ. Manage. 172, 112–126. https://doi.org/10.1016/j.jenvman.2016.02.013.

Molina-Terrén, Domingo M., Xanthopoulos, Gavriil, Diakakis, Michalis, Ribeiro, Luis, Caballero, David, Delogu, Giuseppe M., Viegas, Domingos X., Silva, Carlos A., Cardil, Adrián, 2019. Analysis of forest fire fatalities in Southern Europe: Spain, Portugal, Greece and Sardinia (Italy). Int. J. Wildl. Fire 28 (2), 85. https://doi.org/10.1071/WF18004.

Moreira, Francisco, Ascoli, Davide, Safford, Hugh, Adams, Mark A, Moreno, José M, Pereira, José M C, Catry, Filipe X, Armesto, Juan, Bond, William, González, Mauro E, Curt, Thomas, Koutsias, Nikos, McCaw, Lachlan, Price, Owen, Pausas, Juli G, Rigolot, Eric, Stephens, Scott, Tavsanoglu, Cagatay, Vallejo, V Ramon, Van Wilgen, Brian W, Xanthopoulos, Gavriil, Fernandes, Paulo M, 2020. Wildfire

management in Mediterranean-type regions: paradigm change needed. Environ. Res. Lett. 15 (1), 011001. https://doi.org/10.1088/1748-9326/ab541e.
Moritz, Max A., Batllori, Enric, Bradstock, Ross A., Gill, A. Malcolm, Handmer, John, Hessburg, Paul F., Leonard, Justin, McCaffrey, Sarah, Odion, Dennis C., Schoennagel, Tania, Syphard, Alexandra D., 2014. Learning to coexist with wildfire. Nature 515 (7525), 58–66.
Otero, I., Nielsen, J.Ø., 2017. Coexisting with wildfire? Achievements and challenges for a radical social-ecological transformation in Catalonia (Spain). Geoforum 85, 234–246. https://doi.org/10.1016/j.geoforum.2017.07.020.
Palaiologou, Palaiologos, Ager, Alan A., Nielsen-Pincus, Max, Evers, Cody R., Kalabokidis, Kostas, 2018. Using transboundary wildfire exposure assessments to improve fire management programs: a case study in Greece. Int. J. Wildl. Fire 27 (8), 501. https://doi.org/10.1071/WF17119.
Palaiologou, Palaiologos, Kalabokidis, Kostas, Troumbis, Andreas, Day, Michelle A., Nielsen-Pincus, Max, Ager, Alan A., 2021. Socio-Ecological Perceptions of Wildfire Management and Effects in Greece. Fire 4 (2), 18. https://doi.org/10.3390/fire4020018.
Parisien, Marc-André, Barber, Quinn E., Hirsch, Kelvin G., Stockdale, Christopher A., Erni, Sandy, Wang, Xianli, Arseneault, Dominique, Parks, Sean A., 2020. Fire deficit increases wildfire risk for many communities in the Canadian boreal forest. Nat. Commun. 11 (1) https://doi.org/10.1038/s41467-020-15961-y.
Parisien, M.A., Dawe, D.A., Miller, C., Stockdale, C.A., Armitage, O.B., 2019. Applications of simulation-based burn probability modelling: A review. Int. J. Wildl. Fire 28, 913–926. https://doi.org/10.1071/WF19069.
Pastor, Elsa, Muñoz, Juan Antonio, Caballero, David, Àgueda, Alba, Dalmau, Ferran, Planas, Eulàlia, 2020. Wildland-Urban Interface Fires in Spain: Summary of the Policy Framework and Recommendations for Improvement. Fire Technol. 56 (5), 1831–1851. https://doi.org/10.1007/s10694-019-00883-z.
Pausas, Juli G., Bond, William J., 2020. Alternative Biome States in Terrestrial Ecosystems. Trends Plant Sci. 25 (3), 250–263. https://doi.org/10.1016/j.tplants.2019.11.003.
Pellicer, F., 1993. El color en el lenguaje cartográfico. Geographicallia 30, 309–320.
Penman, T.D., Nicholson, A.E., Bradstock, R.A., Collins, L., Penman, S.H., Price, O.F., 2015. Reducing the risk of house loss due to wildfires. Environ. Model. Softw. 67, 12–25. https://doi.org/10.1016/j.envsoft.2014.12.020.
Plucinski, Matt P., 2019. Fighting Flames and Forging Firelines: Wildfire Suppression Effectiveness at the Fire Edge. Curr. For. Reports 5 (1), 1–19. https://doi.org/10.1007/s40725-019-00084-5.
Plucinski, Matt P., 2012. Factors Affecting Containment Area and Time of Australian Forest Fires Featuring Aerial Suppression. For. Sci. 58 (4), 390–398. https://doi.org/10.5849/forsci.10-096.
R Core Team, R Development Team Core, 2017. R: A Language and Environment for Statistical Computing.
Raftery, Adrian E., Zimmer, Alec, Frierson, Dargan M.W., Startz, Richard, Liu, Peiran, 2017. Less than 2 °C warming by 2100 unlikely. Nat. Clim. Chang. 7 (9), 637–641. https://doi.org/10.1038/nclimate3352.
Regnauld, N., McMaster, R.B., 2007. A synoptic view of generalisation operators. In: Generalisation of Geographic Information. Elsevier Science BV, pp. 37–66.
Reimer, Jonathan, Thompson, Dan K., Povak, Nicholas, 2019. Measuring Initial Attack Suppression Effectiveness through Burn Probability. Fire 2 (4), 60. https://doi.org/10.3390/fire2040060.
Rodrigues, M., Alcasena, F., Vega-García, C., 2019. Modeling initial attack success of wildfire suppression in Catalonia. Spain. Sci. Total Environ. 666, 915–927. https://doi.org/10.1016/j.scitotenv.2019.02.323.
Rodrigues, M., de la Riva, J., 2014. An insight into machine-learning algorithms to model human-caused wildfire occurrence. Environ. Model. Softw. 57, 192–201. https://doi.org/10.1016/j.envsoft.2014.03.003.
Rodrigues, Marcos, Trigo, Ricardo M., Vega-García, Cristina, Cardil, Adrián, 2020. Identifying large fire weather typologies in the Iberian Peninsula. Agric. For. Meteorol. 280, 107789. https://doi.org/10.1016/j.agrformet.2019.107789.
Rodríguez y Silva, Francisco, Molina Martínez, Juan Ramón, González-Cabán, Armando, 2014. A methodology for determining operational priorities for prevention and suppression of wildland fires. Int. J. Wildl. Fire 23 (4), 544. https://doi.org/10.1071/WF13063.
Salis, Michele, Ager, Alan A., Alcasena, Fermin J., Arca, Bachisio, Finney, Mark A., Pellizzaro, Grazia, Spano, Donatella, 2015. Analyzing seasonal patterns of wildfire exposure factors in Sardinia. Italy. Environ. Monit. Assess. 187 (1) https://doi.org/10.1007/s10661-014-4175-x.
Salis, Michele, Arca, Bachisio, Del Giudice, Liliana, Palaiologou, Palaiologos, Alcasena-Urdiroz, Fermin, Ager, Alan, Fiori, Michele, Pellizzaro, Grazia, Scarpa, Carla, Schirru, Matilde, Ventura, Andrea, Casula, Marcello, Duce, Pierpaolo, 2021. Application of simulation modeling for wildfire exposure and transmission assessment in Sardinia. Italy. Int. J. Disaster Risk Reduct. 58, 102189. https://doi.org/10.1016/j.ijdrr.2021.102189.
Salis, Michele, Del Giudice, Liliana, Arca, Bachisio, Ager, Alan A., Alcasena-Urdiroz, Fermin, Lozano, Olga, Bacciu, Valentina, Spano, Donatella, Duce, Pierpaolo, 2018. Modeling the effects of different fuel treatment mosaics on wild fi re spread and behavior in a Mediterranean agro-pastoral area. J. Environ. Manage. 212, 490–505. https://doi.org/10.1016/j.jenvman.2018.02.020.
Scott, J., Burgan, R., 2005. Standard fire behavior fuel models: a comprehensive set for use with Rothermel's surface fire spread model.
Scott, J.H., Thompson, M.P., Calkin, D.E., 2013. A wildfire risk assessment framework for land and resource management.
Syphard, A.D., Brennan, T.J., Keeley, J.E., 2017. The importance of building construction materials relative to other factors affecting structure survival during wildfire. Int. J. Disaster Risk Reduct. 21, 140–147. https://doi.org/10.1016/j.ijdrr.2016.11.011.
Syphard, Alexandra, Keeley, Jon, 2019. Factors Associated with Structure Loss in the 2013–2018 California Wildfires. Fire 2 (3), 49. https://doi.org/10.3390/fire2030049.
Syphard, Alexandra D., Rustigian-Romsos, Heather, Keeley, Jon E., 2021. Multiple-Scale Relationships between Vegetation, the Wildland-Urban Interface, and Structure Loss to Wildfire in California. Fire 4 (1), 12. https://doi.org/10.3390/fire4010012.
Tedim, Fantina, Leone, Vittorio, Amraoui, Malik, Bouillon, Christophe, Coughlan, Michael, Delogu, Giuseppe, Fernandes, Paulo, Ferreira, Carmen, McCaffrey, Sarah, McGee, Tara, Parente, Joana, Paton, Douglas, Pereira, Mário, Ribeiro, Luís, Viegas, Domingos, Xanthopoulos, Gavriil, 2018. Defining Extreme Wildfire Events: Difficulties Challenges, and Impacts. Fire 1 (1), 9. https://doi.org/10.3390/fire1010009.
USDA Forest Service, 2014. The National Strategy: The final phase in the development of the National Cohesive Wildland Fire Management Strategy 93.
Vacca, Pascale, Caballero, David, Pastor, Elsa, Planas, Eulàlia, 2020. WUI fire risk mitigation in Europe: A performance-based design approach at home-owner level. J. Saf. Sci. Resil. 1 (2), 97–105. https://doi.org/10.1016/j.jnlssr.2020.08.001.
Wei, Yu, Thompson, Matthew P., Haas, Jessica R., Dillon, Gregory K., O'Connor, Christopher D., 2018. Spatial optimization of operationally relevant large fire confine and point protection strategies: model development and test cases. Can. J. For. Res. 48 (5), 480–493. https://doi.org/10.1139/cjfr-2017-0271.
Wei, Yu, Thompson, Matthew, Scott, Joe, O'Connor, Christopher, Dunn, Christopher, 2019. Designing Operationally Relevant Daily Large Fire Containment Strategies Using Risk Assessment Results. Forests 10 (4), 311. https://doi.org/10.3390/f10040311.
Wunder, Sven, Calkin, Dave E., Charlton, Val, Feder, Sarah, Martínez de Arano, Inazio, Moore, Peter, Rodríguez y Silva, Francisco, Tacconi, Luca, Vega-García, Cristina, 2021. Resilient landscapes to prevent catastrophic forest fires: Socioeconomic insights towards a new paradigm. For. Policy Econ. 128, 102458. https://doi.org/10.1016/j.forpol.2021.102458.
Zelanski, P., Fisher, M., 2001. Color. Ediciones AKAL.