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Published in:
Ecological Modelling

DOI:
10.1016/j.ecolmodel.2008.11.017

Publication date:
2010

Document version
Publisher's PDF, also known as Version of record

Citation for published version (APA):
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1. Introduction

Forest fires are a major factor of environmental transformation in a wide variety of ecosystems (FAO, 2007). Fires have global impacts (Chuvieco, 2008), affecting forested areas and having an important share in greenhouse gas emissions. Although fire has been historically used as a tool for land use management and many ecosystems are well adapted to fire cycles, recent changes in both climate and societal factors related to fire can transform traditional fire regimes, increasing the negative effects of fire upon vegetation, soils and human values. In this regard, the impact of climate warming on increasing fire frequency and intensity has been documented in several ecosystems (Kasischke and Turetsky, 2006; Westerling et al., 2006). Current climate projections point towards worse conditions in the next decades for most Tropical and Boreal regions (Flannigan et al., 2005).

In addition to global effects, fires have also important local effects, which are commonly associated to fire frequency and intensity, which imply soil degradation, soil erosion, lost of lives, biodiversity, and infrastructures (Omi, 2005). Recent changes in land use management in developed countries, with an increasing abandonment of traditional rural practices (Vélez, 2004; Whitlock, 2004) have implied a remarkable increase of fuel accumulation, which lead to more severe and intense fires, and consequently to higher negative impacts on soils and vegetation resilience.

Within this environmental context, the interest of having better tools for fire prevention and assessment should be emphasized. Fire risk evaluation is a critical part of fire prevention, since pre-fire planning resources require objective tools to monitor when and where a fire is more prone to occur, or when it will have more negative effects. Traditional fire danger systems rely on meteorological indices, based on variables that are routinely measured by weather.
stations. However, atmospheric conditions are only one of the components of fire risk, which should also consider human aspects, fuel loads and moisture status, as well as values at stake. Modelling fuel trends have been proposed to analyze spatial and temporal changes in fire risk conditions (He et al., 2004; Shang et al., 2004).

Traditional fire terminology does not put a strong emphasis on potential damages of fire, but rather on the ignition and propagation potential. For instance, FAO defines fire risk as “the probability of fire starting determined by the presence and activities of causative agencies”. Fire danger, on the other hand, is defined as considering “both fixed and variable factors of the fire environment that determine the ease of ignition, rate of spread, difficulty of control, and fire impact; often expressed as an index” (http://www.fao.org/forestry/site/firemanagement/en/). In both cases, these terms do not clearly distinguish between the physical probability that a fire occurs and the potential damage that it may cause, which is a common practice in natural hazards literature (Bachmann and Allgöwer, 2001).

Following the activities of the European Project Spread, a revision of the traditional fire danger systems was suggested, by including explicitly the vulnerability aspects of fire, which were neglected in previous approaches (Chuvieco et al., 2003). Consequently, a new scheme for fire risk assessment was developed, which included two aspects: fire danger (ignition or propagation potential) and vulnerability (potential damage), being the total risk a product of the two. The Spread fire risk scheme was designed to be scale-independent and therefore applicable to both local and global scales. The system was not fully developed at the initial stage, being the focus the development of methods for generating the input variables. Further process was required to develop consistent methods for data integration and to extend the vulnerability component. These two aspects were developed within another research project (named Firemap) and will be the main objective of this paper. The paper will present the conceptual scheme for fire risk assessment, then it will briefly comment the methods that were used to generate the risk variables, thirdly it will propose techniques for data integration, and it will finally present the results of the initial validation process.

2. Methods

2.1. Fire risk scheme

The fire risk assessment method that we proposed in this paper is based on considering fire occurrence probability and potential damages (Fig. 1). The former is named fire danger throughout this paper, and considers the potential that a fire ignites or propagates. The two main sources of ignition, human and natural, were considered. The former is undoubtedly the most important worldwide (FAO, 2007), but fires caused by lightning are also very relevant in some regions (Nieto et al., in press). In addition to ignition sources, the moisture status of plants was also considered, since plants are the main ignition material in a forest fire. The propagation component of fire danger was associated to the fire spread potential, which is a result of fuel amount and continuity, plus favourable terrain and weather conditions (mainly wind speed).

The second group of fire risk conditions was associated to the vulnerability component, which is the assessment of potential damages caused by the fire. The negative effects of fire were divided in three aspects: socio-economic values (properties, wood resources, recreational importance, carbon stocks, etc.), degradation potential (soil and vegetation conditions), and landscape value (uniqueness, conservation status, etc.).

To obtain an operational assessment of fire risk conditions following the proposed scheme, the following steps were required:

a. Generation of risk factors, using a common geographical unit. A target scale and spatial resolution needs to be defined, in relation to what sources of data are available.

b. Conversion of risk factors to a common risk scale. To integrate the input risk variables, the original measurement scale of each input variable should be first converted to a common risk metric.

c. Development of criteria to integrate risk factors. The different input variables have different impacts on fire risk conditions. Identifying which are more relevant and how they should be weighed to generate synthetic indices is a critical phase in risk assessment.

Since fire risk is a spatial and temporal process, it should be addressed both spatially and temporally. The use of geographic information system (GIS) is quite obvious in this regard, since these tools are ideal to manage spatial information, provide adequate spatial processing and visualization of results. For this reason, several previous studies on fire risk estimation have been based on GIS (Yool et al., 1985; Chuvieco andCongalton, 1989; Chou, 1992; Abhineet et al., 1996; Chuvieco and Salas, 1996; Castro and Chuvieco, 1998; Vasconcelos et al., 2001; Nourbakhsh et al., 2006). To reduce the total length of the paper, the generation of the input variables will be presented briefly, and will refer to more extended publications for details (Table 1).

2.2. Study regions

Several research groups working on Mediterranean conditions participated in developing the Firemap project. Four study areas were finally selected to develop the methods of data generation and integration (Fig. 2). Three of them are autonomous regions of Spain: Aragon with 47,719 km²; Madrid, with 8028 km², and Valencia with 23,255 km², while the fourth is a province of Andalusia (Huelva, 10,148 km²). Total area covered for the four regions is 89,131 km², which accounts for 18% of the total area of Spain. Following end-user recommendations, the minimum mapping unit was fixed at 1 km², using as a reference the standard UTM grid. The regions were selected to provide a good assortment of Spanish various fire conditions. For instance, Aragon has the most important proportion of natural-caused fires and one of the lowest population densities in the country, while Madrid has the highest population density and it is the most urbanized region of Spain. Huelva is still a rural-oriented area, but has a strong contrast between the coastal region and the interior highlands. Valencia suffers the largest forest fires as an average, with an important tourist pressure in the coast and notable forest resources in the interior. Climatic and ecological characteristics are also quite diverse, within the general characteristics
Table 1
Input factors for the fire risk assessment system.

<table>
<thead>
<tr>
<th>Factor</th>
<th>Input data</th>
<th>Method</th>
</tr>
</thead>
<tbody>
<tr>
<td>Human (Vilar et al., 2008)</td>
<td>Historical occurrence</td>
<td>Logistic regression</td>
</tr>
<tr>
<td>Lightning (Nieto et al.,</td>
<td>Demographic data</td>
<td></td>
</tr>
<tr>
<td>in press)</td>
<td>Vegetation—DTM</td>
<td></td>
</tr>
<tr>
<td>Dead fuels moisture content</td>
<td>Meteorological data</td>
<td>Linear regression analysis</td>
</tr>
<tr>
<td>Live fuels moisture content</td>
<td>Satellite images</td>
<td>Statistical fitting</td>
</tr>
<tr>
<td>Propagation danger</td>
<td>Fuel type maps</td>
<td>Inversion of RTM</td>
</tr>
<tr>
<td>Socio-economic values</td>
<td>Forest maps</td>
<td>Empirical models</td>
</tr>
<tr>
<td>Degradation potential</td>
<td>Soil maps</td>
<td>Ecological models</td>
</tr>
<tr>
<td>Landscape value</td>
<td>Protected areas</td>
<td>Landscape pattern</td>
</tr>
</tbody>
</table>

of Mediterranean areas. Generally speaking, Madrid and Aragon are more continental, while Huelva and Valencia have more maritime influences, being Huelva more rainy and with milder summer temperatures than Valencia.

2.3. Generation of risk variables

2.3.1. Modelling the human factors of fire ignition

In most countries human activities are in one way or the other, the main responsible for fire ignition. Humans have used fire historically for different purposes: light, heat, cooking, land clearing, etc., and still have a critical impact on fire regimes and vegetation distribution (Pyne, 1995). In Mediterranean areas, human factors cause more than 90% of fires (Leone et al., 2003). In Spain, 96.1% of all fires are human-caused (Dirección General de Biodiversidad, 2006).

In spite of the importance of these human aspects, little work has been devoted to this issue, maybe because of the complexity of predicting human behaviour, both in space and time. Most frequently, the studies have focused on variables related to land use or land use-change (rural abandonment, agricultural–forest interface or urban–forest interface), population trends, rural activities, potential conflicts that may lead to vengeances or arson (unemployment, enforcement of conservation areas, reforestation in traditional pastured areas, etc.) (Vega-García et al., 1995; Cardille et al., 2001; Leone et al., 2003; Martínez et al., 2009).

The approach to consider human factors in fire risk assessment has been commonly based on statistical models, which have tried to explain historical human-caused fire occurrence from a set of independent variables (Martell et al., 1989; Chou et al., 1993; Chuvieco et al., 2003; Martínez et al., 2004). Most commonly, those variables are previously mapped at a similar spatial resolution of the fire databases, using a GIS. Logistic regression analysis has been frequently used for prediction and explanation of human-caused fire occurrence (Chou et al., 1993; Vega-García et al., 1995; Vasconcelos et al., 2001; Martínez et al., 2009).

For this project, the analysis of human risk conditions were firstly based on selecting the critical variables associated to human-cause fires in Spain, following a detailed reviewed of specialized literature. General factors commonly identified by previous studies needed to be approached using single variables, which should be available for all study sites. For instance, fires associated to negligence or arson were approached by considering distances to roads and railroads, electric lines and military establishments, while the factor associated to recreational land use was approached by the presence of urban–wildland interfaces, hotels and cabins, and camping sites.

In a second phase, variables expressing each factor were mapped at the target spatial resolution of the fire risk assessment system.

![Fig. 2. Location of the study areas.](image-url)
Table 2

<table>
<thead>
<tr>
<th></th>
<th>Madrid Low occurrence</th>
<th>Madrid High occurrence</th>
<th>Valencia Low occurrence</th>
<th>Valencia High occurrence</th>
<th>Huelva Low occurrence</th>
<th>Huelva High occurrence</th>
<th>Aragon Low occurrence</th>
<th>Aragon High occurrence</th>
</tr>
</thead>
<tbody>
<tr>
<td>Accuracy</td>
<td>75.4%</td>
<td>65.7%</td>
<td>79.4%</td>
<td>57.4%</td>
<td>92.4%</td>
<td>76.4%</td>
<td>82.0%</td>
<td>91.4%</td>
</tr>
<tr>
<td>Global accuracy</td>
<td>70.6%</td>
<td></td>
<td>68.4%</td>
<td></td>
<td>84.4%</td>
<td></td>
<td>86.8%</td>
<td></td>
</tr>
</tbody>
</table>

Table 3

<table>
<thead>
<tr>
<th>Selected variables</th>
<th>Marginal effects (dx/dy)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Buffer forest trails</td>
<td>0.064</td>
</tr>
<tr>
<td>Natural protected areas</td>
<td>0.155</td>
</tr>
<tr>
<td>Urban–wildland interface</td>
<td>0.190</td>
</tr>
<tr>
<td>Change in rural population</td>
<td>-0.105</td>
</tr>
<tr>
<td>Farmers above 55 years</td>
<td>-0.105</td>
</tr>
<tr>
<td>Unemployment rate</td>
<td>0.113</td>
</tr>
<tr>
<td>Hotels</td>
<td>-0.208</td>
</tr>
</tbody>
</table>

Table 4

<table>
<thead>
<tr>
<th></th>
<th>Madrid No ignition</th>
<th>Madrid Ignition</th>
<th>Aragon No ignition</th>
<th>Aragon Ignition</th>
<th>Valencia No ignition</th>
<th>Valencia Ignition</th>
<th>Huelva No ignition</th>
<th>Huelva Ignition</th>
</tr>
</thead>
<tbody>
<tr>
<td>Accuracy</td>
<td>68.4%</td>
<td>72.7%</td>
<td>71.0%</td>
<td>67.0%</td>
<td>69.6%</td>
<td>65.1%</td>
<td>81.0%</td>
<td>80.7%</td>
</tr>
<tr>
<td>Global accuracy</td>
<td>68.6%</td>
<td></td>
<td>70.8%</td>
<td></td>
<td>69.3%</td>
<td></td>
<td>87.0%</td>
<td></td>
</tr>
</tbody>
</table>
2.3.3. Ignition potential associated to fuel moisture content status

Fuel moisture content (FMC) is a critical variable to estimate ignition and propagation danger, since the amount of water in the vegetation is inversely related to ignition potential and rate of spread (Nelson, 2001). Following a common approach in forest fire literature, the estimation of FMC was divided in this project between dead and live components. The former were estimated from meteorological variables and the later from satellite images.

The estimation of FMC for dead materials lying on the forest floor (leaves, branches, and debris) is included in most operational fire danger rating systems (Camia et al., 2003). It is most commonly estimated from meteorological variables, since dead fuels change their water content in parallel to atmospheric conditions. Weather changes affect the degree of water evaporation and absorption, especially temperature, rainfall and wind speed (Viney, 1991). The estimation of dead FMC for this project was performed from an empirical approach, based on field sampling developed between 1998 and 2003 in Central Spain (Aguado et al., 2007). The independent variables in this case were two moisture codes routinely used in fire danger estimation: the Fine Fuel Moisture Code (FFMC) and the 10-h code, the former being part of the Canadian and US fire danger systems, respectively. Similar results were obtained from the two moisture codes, but finally the 10-h code was selected, since it does not require wind speed as an input and therefore it is easier to compute. Once the empirical relations were established, they were extended to a grid of 1 km x 1 km resolution, interpolated from the data of the European Centre for Medium Range Weather Forecasting (ECMWF)’s using local algorithms. The interpolation algorithm took into account horizontal distances between the grid point and the surrounding stations (quadratic inverse distance algorithm).

The effect of altitude of each grid point over the value of the variable (temperature or humidity) was also considered (Aguado et al., 2007). The estimation of dead FMC was computed everyday, based on 12 (noon) forecasted data from the 8 a.m. prediction (Fig. 3).

Regarding the estimation of FMC of live species, satellite remote sensing was used as an input. The use of satellite data in live FMC estimation has been discussed by different authors in the last years (Chuvieco et al., 2004b; Danson and Bowyer, 2004; Maki et al., 2004; Dennison et al., 2005; Riaño et al., 2005; Stow et al., 2005). In spite of the difficulty of extracting the influence of water absorption over other factors affecting plant reflectance, several studies have found good relationships, especially in grasslands and some shrub species. Two approaches were used in this project, one based on empirical models for NOAA-AVHRR images, using results from previous projects (Chuvieco et al., 2004b), and the other one based on simulation models for Terra-MODIS data (Yebra et al., 2008). The empirical method was found inappropriate for very dry years, such as 2005, when high overestimations were found. Therefore, a revision of the empirical method was proposed. The new functions took into account the rainfall conditions of the Spring season to choose whether a dry or normal year equation should be applied. The outputs provide a more consistent estimation of FMC for contrasting years than a single model (Garcia et al., 2008).

The second approach to estimate FMC of live species was based on the inversion of simulation models, based on the radiative transfer function (RTM, Pinty et al., 2004). The inputs were an 8-day composite of the first seven reflectance bands of MODIS (MOD09 product: Vermote and Vermeulen, 1999), as well as the vegetation indices and the leaf area index product derived from the same sensor MOD15 (Knyazikhin et al., 1999). The performance of
RTM versus empirical models showed similar accuracies for grasslands (root mean square error 24.5 and 27.4%, respectively), and worst accuracy for shrublands (23.04 and 14.30%, respectively). Considering the greater accessibility to AVHRR images and the good performance of the calibrated models, finally the empirical model based on these images was used in this project for the estimation of live FMC. To avoid cloud coverage and off-nadir observations, an 8-day compositing technique based on maximum daily temperatures was used (Chuvieco et al., 2005). Therefore, the estimation of live FMC was updated every 8-day.

2.3.4. Propagation potential

Most fire spread simulation models have been designed for local conditions and for active fires that have occurred or have been simulated to occur. For this project, it was intended to produce an estimation of the average propagation potential of each cell, assuming a fire may occur anytime in any cell of the study areas. Another challenge was that fire propagation values should be calculated for coarse grid cells, since our model was addressed to regional scales, which is uncommon in fire behaviour models.

Within these two limitations, average propagation conditions were simulated using the Behave program (Andrews and Chase, 1990). A total of 5525 simulations were run for the 13 fuel types defined within this program, by modifying systematically the slope gradients, from 0% to 90%, and the wind speeds, from 4 km/h to 20 km/h. Standard values of FMC were considered: 5% for 1-h moisture fuels, 10% for 10-h moisture fuels, 12% for 100-h moisture fuels and 50% for live fuels (Vélez, 2000; Martín Fernández et al., 2002). Those input conditions were selected by considering the worst-case scenario, that is the fire is potentially propagated along the maximum slope gradient and the wind speed is the average of the maximum speeds for the summer time.

The simulated values of flame length and rate of spread were averaged for each fuel type and slope interval, as to generate a potential propagation map of the study sites. Fuel type models were derived from the forest inventory maps, by selecting the most common fuel in the target cell size of 1 km × 1 km. Slope intervals were computed from the 250 m × 250 m digital terrain model of Spain, originally derived from 1:200,000 scale topographic maps.

2.3.5. Socio-economic values

In the Firemap project, topics associated to values at stake (vulnerability) were divided in two groups: those associated to economic and social factors, and those related to ecological components. The former were intended to evaluate what potential damages from the fire could be related to losses of wood products, hunting revenues, recreational and tourist resources. Additionally, the potential economic impacts of carbon sequestration, soil erosion and landscape conservation were taken into account.

Different approaches were used for deriving each factor. The “tangible” resources were evaluated using direct methods, such as the market price, the age of the forest stand and the rotation length. The wood resources were assessed following a mixture procedure that considers the American approach (only natural regeneration is considered) and the European one (man-induced regeneration, as well). The “intangible” resources were evaluated using indirect methods, such as the cost-travel and the contingent valuation methods. The former has been used to assess the recreational value of the landscape, while the latter was the basis to evaluate the cost of no-use and wildlife conservation of endangered species. The values associated to hunting and CO2 sinks were priced according to the forest inventory.

To illustrate the methods, two examples can be comment in more detail, one of the tangible resources and the other on the intangible ones. An example of the tangible resource is the use of the acorn of evergreen oaks, which is an important component for feeding high-quality Iberian pig species. The sustainable use of this resource requires computing the adequate density of animals per hectare, which was based on the density of oaks and their sanitary status. Once the overall production was estimated, the potential damage of losing those resources by a forest fire was computed following:

\[ V = \frac{P \times (1 + i)^{(T-e)} - 1}{(1 + i)^{(T-e)}} \]

where \( V \) is the assessment of potential losses, \( P \) the production of acorns (kg ha\(^{-1}\)), \( R \) the price (€ kg\(^{-1}\)), \( i \) the yearly rate of devaluation, \( T \) the rotation for the oaks (in years) and \( e \) is the age of the species for the year of the fire (in years).

Another example of the socio-economic vulnerability assessment refers to an intangible resource, which is the valuation of recreational resources. These resources were assessed using the travel-cost model (Riera-Font, 2000). A demand function was derived to account for the preferences of population to access different natural areas. The demand function was formulated as:

\[ D_j = f(C_{ij}, R_j, V_j, E_{ij}, T_j) \]

where \( C_{ij} \) is the number of days where visitor “i” goes to place “j”, \( C_j \) the cost associated to move to “j” for visitor “i”, \( R \) the rent of visitor “i” (according to four ranges), \( V_j \) the number of times that visitor “i” goes to place “j”, \( E \) a weighting factor on whether the visitor is willing to pay a fee to enter the natural area “j”, and \( I \) is the qualitative importance of forest areas for visitor “i” (questionnaire scale from 1 to 4). The formula is additionally weighted according to the number of visitors in each natural area and provides a total estimation of economic interest for each cell of the study areas. Wood resources were estimated from current cost of wood products and different scenarios of potential fire intensity level. Net productivity and reforestation costs were also considered.

The economic assessment of all the resources considered in the socio-economic vulnerability was included into a dedicated geographic information system. Some of the variables were computed in quantitative terms (mostly in € ha\(^{-1}\)), while others were calculated in qualitative values (vulnerability categories). Obviously, the more intense the fire, the more important the damages, and therefore the model considered also different fire behaviour scenarios. Six fire intensity levels were considered and average conditions were considered for the final evaluation of socio-economic resources at stake.

2.3.6. Degradation potential

The vulnerability associated to ecological factors was focused on the assessment of vegetation response to fire effects. This response was set up for two different time periods: short term (less than 1 year), focused on identifying the most erodible areas, and medium term (25 years), to identify changes in vegetation structure and composition caused by the fire. As a result of both, a synthetic index of the degradation potential associated with fire was obtained (Alloza et al., 2006). Since vulnerability evaluation needs to be done before a fire occurs, no previous knowledge of fire characteristics and post-fire climatology is available. Consequently, risk scenarios need to be created. In our case, we chose the worst-case scenario according to typical Mediterranean conditions: the fire occurs in summer, the fuel has low humidity and post-fire climatic conditions are similar to the historical average.

For the short-term evaluation, the post-fire ecosystem response capacity was determined by physical environment characteristics in terms of erodibility and characteristics of the affected vegetation (a comprehensive scheme of the evaluation process is included in Fig. 4).
Erodibility refers to the potential erosion as a result of post-fire vegetation loss. In spite of the numerous modifications and criticism on the Universal Soil Loss Equation (USLE) structure, it still constitutes a reference to assess the magnitude of soil loss in burnt areas (Giovannini, 1999). Consequently, the same factors considered by the USLE (soil erodibility, slope, vegetation and climate) were considered in our model. Soil erodibility analysis was based on organic matter content, surface structure and soil crust risk. The slope factor was quantified from the digital elevation models, and the post-fire cover factor, by estimating density and structure of the vegetation communities from the National Forest map. For the climate factor, the Fournier index was used as an indicator of the climate erosive ability. Due to data limitations, a qualitative approach was finally selected by classifying erodibility in three categories: high, medium and low sensitivity to fire effects.

Vegetation response ability is critical to explain post-fire soil erosion, since a minimum vegetation cover of 30–40% is commonly accepted as the limit protective role of vegetation against erosion (Francis and Thornes, 1990). To approach vegetation response, the post-fire ecological strategies of different functional groups were considered, like the resprout ability, the seed bank persistence or the growth or dispersal ability (Lavorel et al., 1999; McIntyre et al., 1999). To predict the response ability, post-fire reproductive strategy was considered as a predictive attribute, based on the information available of long-term post-fire regeneration patterns in Mediterranean forest (Baeza et al., 2007; Baeza and Vallejo, 2008). Based on the National forest map, the main vegetation communities were grouped according to the vertical composition structure (trees and/or shrubs) and the reproductive strategy. For each community, a vulnerability value was assigned as the inverse of its response ability to the short-term effects (e.g. seeder shrubland = very high; resprouter shrubland = low; deficient seeder tree covered + seeder shrubland = very high; resprouter tree covered + mixed shrubland = medium vulnerability). The climatic limits to post-fire regeneration were based on historical water deficit indicators.

The integration of the different components of post-fire short-term degradation potential was determined by soil erodibility and vegetation vulnerability and water limitations (Fig. 4). Scenarios of fire intensity were estimated for the Rothermel’s standard fuel models (Anderson, 1982), contrasted on experimental fires (Baeza et al., 2002) and fire simulations carried out with the FARSITE fire simulator (Finney, 1998). The final characterization was: 1, 8, 9 = low intensity; 2, 5, 6, 7, 10, 11 = medium intensity, and 3, 4, 12, 13 = high intensity.

In the medium-term, 25 years after the fire, the affected vegetation community’s vulnerability was determined by its ability to persist with no substantial changes (community structure, specific composition and relative presence of the species). Taking into account the vegetation communities’ grouping carried out and the fire historical frequency, ecological vulnerability in the medium term was rated: seeder shrubland = medium; resprouter shrubland = low; deficient seeder tree covered + seeder shrubland = high; resprouter tree covered + mixed shrubland = low vulnerability. The synthetic index of the degradation potential is obtained by qualitative cross-tabulation between the short and medium term with four categories (low–moderate–high–extreme).

2.3.7. Landscape value

Landscape value was the third component to account for fire vulnerability. Fire managers take into account the intrinsic quality of the landscape to rank the pre-fire planning, obviously along...
with other variables associated to human settlements and potential life threads. The evaluation of landscape characteristics has been approached by many authors in the last years, including a wide range of criteria: ecological (Kato et al., 1997; Nakagoshi and Kondo, 2002), aesthetic, population preferences, visual properties (Martínez-Vega et al., 2003; Ariaza et al., 2004). For the Firemap project, the consideration of landscape properties in fire vulnerability assessment was approached from a weighed combination of the intrinsic value of the landscape and the legal status of protected areas (Martínez-Vega et al., 2007).

The intrinsic value of the landscape took into account common procedures in landscape evaluation, considering degree of “uniqueness”, proximity to the “natural” conditions and pattern conditions (diversity, patch connectivity and mixture). The input variables for measuring those landscape properties were the CORINE land cover map (Büttner et al., 2000) and the potential vegetation map of Spain.

The consideration of legal protection figures for each cell was measured as whether it was within any of the designated conservation areas (National and Regional parks, Natural reserves, Nature 2000 selected areas, sites of Community Importance and other European conservation figures). Additionally, the communal forests were also considered. Each protected area was evaluated for fire vulnerability by local managers. For the integration of single evaluation values, a weighed sum based on fire’s experts knowledge was computed.

Final results showed an important proportion of the study areas covered by high or very high vulnerability to wildland fires. Areas within the highest ranks covered 24% of Huelva, 15% of Madrid, 12% of Aragon and 11% of Valencia. The integration models have been evaluated qualitatively by the forest services during the summer of 2007, with satisfactory agreement with their own evaluations.

2.4. Model integration

2.4.1. Creating a common danger scales

Once the input risk variables were generated, two additional tasks were required to obtain an integrated fire risk index. On the one hand, the input variables needed to be converted to a common risk scale; on the other hand, they should be properly weighed, so the importance of the different factors was taken into account.

Several methods have been proposed to find common scales of fire risk, being variable normalization, qualitative categorization and probabilistic approaches the most common (Chuvieco et al., 2003). Variable normalization generates a common scale by converting each variable to a zero-one range, using either the minimum and maximum value, or the mean and standard deviation of the input variable. Qualitative groups imply to convert the original scale to a categorical or ordinal one, using categories such as low, medium and high risk. Finally, the probabilistic approach requires to model the variables using any of the standard probability functions (normal, Poisson, Binary, etc.).

For this project, it was not possible to obtain a common risk scale for all the input variables, especially for the complexity to quantify the ecological vulnerability. While further developments find an appropriate way to solve this problem, as a first step vulnerability values were categorized in four ordinal groups: low, medium, high and extreme. This decision conditioned the rest of the integration scheme, since the socio-economic vulnerability needed to be expressed in similar categories. Cross tabulation process was carried out to obtain final ratings, following end-users knowledge.

Regarding the fire danger branch of the fire risk scheme, all the variables were converted to a 0–1 scale using probability functions. For the consideration of the causes (human and lightning), the estimation models were based on logistic regression analysis and, therefore, the predictions were already expressed in probabilistic terms. For the fuel moisture content, the conversion of FMC to ignition potential (IP, 0–1 scale) was based on a physical model, using the concept of moisture of extinction (ME: Simard, 1968). This value expresses the maximum moisture value above which a fire is not sustained, and differs for each fuel type. The conversion from FMC to IP was based on a linear relation from the FMC minimum value found in the historical data series (IP = 1) to ME (IP = 0.2) (Chuvieco et al., 2004a). Strictly speaking, the ignition potential of a fuel when FMC equals to ME should be 0. However, in our project a conservative approach was adopted and the probability of a fuel with FMC equals to ME was set to 0.2, to avoid eliminating areas with mixed fuels.

Finally, the conversion of the propagation variables (rate of spread and flame length) to a propagation potential danger was based on a normalization procedure. The normalization was based on the cumulative proportion of both rate of spread and flame length in all grid cells of the study areas. For each cell, the maximum probability value between rate of spread and flame length was selected as representative of the worst-case conditions.

2.4.2. Integration of risk indices

Once the risk variables have a common scale of danger, they can be combined in many different ways and using a wider range of techniques: qualitative cross-tabulation, multicriteria evaluation, regression techniques or probabilistic models (Chuvieco et al., 2003). Different choices were made for this project.

The integration of the causative agents (human and lightning) was based on the Kolmogorov probabilistic rule (Taratola, 2005), which indicates that the probability of two independent events can be expressed as

\[ P(A \cup B) = P(A) + P(B) - P(A)P(B) \]

where \( P(A \cup B) \) is the integrated probability, \( P(A) \) the probability of ignition derived from human variables and \( P(B) \) is the probability of ignition derived from lightning.

The integration of live and dead FMC was performed by averaging both FMC ignition potential values, weighted by the percentage cover of both dead and live fuels.

For the integration of causative agents and FMC a multicriteria evaluation technique (Gomez-Delgado and Barredo-Cano, 2006) was adopted. It was assumed that high risk probability should be associated to situations when both high probability of having causative agents and FMC ignition potential occur. Assuming that both of these two variables are expressed in a Cartesian axis, the distance to the maximums should be a good indicator of risk conditions, since that point expresses the highest probability of both factors (Fig. 5a).

In the case of the integration between ignition and propagation danger, a similar approach was adopted, although in this case it was assumed that the worst conditions would occur either when the maximum ignition or propagation danger occur. Therefore, in this case the maximum danger values should be those more distant from the origin (Fig. 5b). In both, the integration of ignition danger components, and between ignition and propagation danger, the dynamic factors (FMC) were weighed higher (four times) than the static factors (human, lightning and propagation), as to be more sensitive to variables than change rapidly.

For vulnerability variables, the criterion to convert the original quantitative scale of the socio-economic aspects and landscape values to a risk scale was based on qualitative weighing. The final integration of the vulnerability component was based on four qualitative risk categories (low–moderate–high–extreme), as to put those factors in relation to the soil degradation factor, which was already expressed in these four categories. A similar weigh was applied to the three factors considered (socio-economic, degradation potential and landscape value), since they were considered
2.5. Development of a dedicated web-mapping service

The Firemap project was intended to develop operational methodologies for fire managers. Therefore, the participation of end-users was always encouraged. To facilitate this participation, a dedicated web mapping service was developed within the project, using public domain software (mapserver, http://mapserver.gis.umn.edu/, last accessed 22 October 2008). The final server was tested during the fire season of 2007 (June to September), and it was successfully reported by the end-users. It included all the input risk variables and integrated indices, plus several vector variables as auxiliary information. Zoom, roam, consults, and download facilities were created (http://www.geogra.uah.es:8080/cartofire/index.php, last accessed on 22 October 2008).

2.6. Validation

Two types of assessment should be considered in a fire risk framework: the validation of the input risk variables and the validation of the final risk indices. The former assessment should be associated to the actual variable, rather than to the fire occurrence values. For instance, the FMC estimation should be assessed against FMC field measurements and not in relation to fire statistics, since FMC is not the only factor affecting fire ignition or propagation. In fact, even with very low values of FMC fires will not occur, in the absence of a causative agent. Consequently, validating FMC with fire statistics may be misleading.

However, the assessment of integrated indices should be based on fire statistics, since an integrated index should consider the main factors of risk and therefore should properly predict fire ignition and/or propagation. Since fire occurrence changes in space and time, the validation of integrated indices should be done with long time series, because short periods may bias some of the theoretical assumptions that are required to build the model. In spite of this, a first approximation of validating fire risk indices may be based on shorter time periods, when enough spatial samples are available. In this case, the fire risk server was server for the summer of 2007 in the four study regions. The first assessment is therefore based on ignition points collected within 4 months of daily data. The total sample was more than 7 million observations (60,000 cells of 1 km² times 120 days).

This preliminary assessment was focused on evaluating the existence of significant differences between the risk values of fire and non-fire cells.
no fire cells. For validation purposes, two indices were considered, the ignition danger, which included human and lightning factors, and the integrated danger, which included ignition and propagation danger. The vulnerability components were not considered, because they are not related to fire occurrence, but rather to the impacts of fire once it occurs. They could not be assessed, since estimations of fire effects are not routinely collected by official fire statistics.

The assessment was based on fire reports generated by the regional forest fire services involved in the Firemap project. Ignition points extracted from GPS survey were available for most of the fires, as well as the starting date and time, and burned area. Total ignition points that were used for validation were 173 in Madrid, 111 in Huelva, 188 in Aragon, and 158 in Valencia.

Several statistics to estimate significance of differences between fire and non-fire cells were computed: (1) the distances of Mahan-
Ianobis; (2) the Mann–Whitney U-test (Mann and Whitney, 1947); (3) the Nagelkerke $R^2$ coefficient from logistic regression fittings for each integrated index (Andrews et al., 2003). Processing was done using the R statistical software (R Development Core Team, 2007).

Tables 5–7 show the results of this validation. The two integrated indices showed similar values in the regions, although some discrepancies were observed. Ignition danger generally shows higher Mahalanobis distances than integrated Danger. However, the results were very close between the two in Huelva (with the highest values among the different regions), and Valencia (the worst). The $U$ values confirm those results, since both Ignition danger and Integrated danger provide significant differences in all study regions. The results are poorer for Valencia than for other regions. The logistic regression analysis showed similar trends as the $U$ test, which

![Box graphs showing differences in the integrated danger for cells with and without fires during the summer of 2007.](image-url)
significant differences for all regions and indices. The two risk components show higher values for fire cells than for non-fires, showing the potential of these indices to predict fire occurrence in very different regions, although a wide diversity of risk values within non-fire areas was observed (Figs. 6 and 7).

3. Discussion and conclusions

The paper has proposed an integration framework for fire risk evaluation. The system was based on two groups of factors: those associated to the probability that a fire occurs and those related to the potential damages of fires. Within the former, causative agents were considered, as well as fuel moisture status and propagation conditions. This terminology is quite innovative in the fire risk assessment literature, which has traditionally relied on monitoring weather conditions. Most operational fire danger systems are restricted to meteorological danger indices (San Miguel-Ayanz et al., 2003). The potential changes in fire danger conditions associated to climate warming may be easily estimated using these meteorological danger indices, based on the different climate scenarios currently available (Gillett et al., 2004). Recent papers have modelled spatial and temporal changes in fuel characteristics, leading to changes in fire risk conditions (He et al., 2004; Shang et al., 2004). These prototypes are based on modelling biophysical conditions and fire history leading to fuel accumulation. They are very useful to predict future scenarios and propose fuel treatments for fire risk reduction.

Our model does not provide yet the capacity of modelling future conditions, but it is more comprehensive than the former approaches, since it includes socio-economic aspects and vulnerability factors. Although most fire managers recognize the importance of human factors, there are not operational systems including this component, either by lack of input information or the difficult integration between socio-economic and weather factors. This paper has addressed this issue and proposed mechanisms to integrate human characteristics into integrated risk indices. Similarly, the vulnerability aspects have not been considered in operational fire danger indices, but they are a relevant part of assessment systems for others natural hazard (earthquakes, floods, volcano eruptions, etc.). The potential damages associated to fire occurring in a particular area and period should lead the decisions on fire suppression, by prioritizing those areas with more valuable resources at stake.

The limited assessment that has been available for this study has shown significant differences between two integrated indices and fire ignition in four study regions located in Spain. These regions have different ecological and fire conditions and may be considered a representative sample of the potential of these indices. However, further assessment is required work is required in other regions and periods to check consistency and generalization potential. Additional work is also needed to improve procedures of data integration, and sensitivity analysis of input variables in the final integration. In spite of those limitations, the scheme proposed in this paper should provide a sound procedure to obtain synthetic and spatially explicit assessment of fire risk conditions, to help improving pre-fire management and to take more appropriate decisions about rehabilitation of areas affected by wildland fires.

Acknowledgements

The Firemap project was funded by the Spanish Ministry of Science and Education (CGL2004-060490C04-01/CLI) through the Environment and Climate program. Very useful comments were received from end-users of the project: Civil Protection, Forest services in Madrid, Aragon, Valencia and Andalusia regions.

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