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ABSTRACT

Fire risk indices are useful tools for fire prevention actions by fire managers. A fire ignition is either the result of lightning or human activities. In European Mediterranean countries most forest fires are due to human activities. However, lightning is still an important fire ignition source in some regions. Integration of lightning and human fire occurrence probability into fire risk indices would be necessary to have a complete picture of the causal agents and their relative importance in fire occurrence. We present two methods for the integration of lightning and human fire occurrence probability models at 1 × 1 km grid cell resolution in two regions of Spain: Madrid, which presents a high fire incidence due to human activities; and Aragón, one of the most affected regions in Spain by lightning-fires. For validation, independent fire ignition points were used to compute the Receiver Operating Characteristic (ROC)-Area Under de Curve (AUC) and the Mahalanobis Distance. Results in Madrid are satisfactory for the human fire occurrence probability model (AUC∼0.7) but less suitable for the lightning and the integrated models. In Aragón the fit for the human model is reasonable (AUC∼0.7) whereas for the integration methods is practically useless (AUC∼0.58).

Key Words: AUC, fire risk, Mahalanobis Distance, probabilistic, fire risk indices, Receiver Operating Characteristic, ROC.

INTRODUCTION

Wildland fires can be considered a significant disturbance factor in many ecosystems (Mooney *et al.* 1981; Pyne 1982). In European Mediterranean countries wildfires play an important ecological role on landscape features. Vegetation communities in these ecosystems are adapted to fire (Moreno 1989). However, in the last

decades socioeconomic, cultural, and political changes have brought important transformations that have caused significant changes in wildfire activity.

Wildfires have important consequences at environmental, ecological, economic, and sociological levels. Because of that, the development of accurate tools to predict wildfire occurrence such as fire risk indices is essential to the establishment of fire prevention actions in order to reduce fire impacts.

According to the Food and Agriculture Organization's (FAO's) terminology, fire risk is defined as the probability of fire starting determined by the presence and activities of causative agencies, while fire danger 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, which is often expressed as an index (http://www.fao.org/forestry/site/firemanagement/en/, April 2009). In contrast with other natural disturbances, fires can theoretically start in any point of space (in the zones covered with vegetation). The probability of ignition depends primarily on the fuel conditions (flammability, moisture content) and the causal agents, which can be human or natural (lightning). Fire Danger Rating indices can be classified in short-term and long-term indices (Chuvieco *et al.* 2003). Short-term estimation of risk is required to take update decisions on fire pre-suppression and suppression activities, while long-term estimation addresses the general, more permanent, planning of fire fighting resources (Chuvieco *et al.* 1999).

Short-term indices are primarily concerned with the most dynamic variables involved in fire danger (weather parameters and fuel moisture content) and should ideally provide daily estimations. Long-term indices refer to the integration of the most stable variables that affect fire ignition and/or fire propagation, such as topography, fuel load and structure, human activities, and climate patters, which can be considered stable, at least during a whole fire season. The term "risk" is used in very different communities and in various situations but seems to be alleged to two meaning complexes: loss, harm, and injury on one side and chance and probability on the other side (Bachmann and Allgöwer 1999).

Chuvieco *et al.* (2003, 2010) proposed that an integrated assessment of fire risk should consider both fire ignition probability as well as the assessment of potential damages (vulnerability of the affected areas). Within the framework of the *Firemap* research project ("Integrated Analysis of Wildland Fire with Remote Sensing and GIS") a wildland fire risk index was developed that integrates the human and environmental factors related to fire ignition (Chuvieco *et al.* 2010). This index has considered the human and lightning fire ignition sources separately; and as a result, independent predictive models for each causative agent have been generated. The main interest of this particular approach was to isolate the main human and biophysical factors that affect fire occurrence as the human factors are frequently masked by the biophysical ones when they are all included in the same model. In order to obtain a final fire ignition probability value, the human and lightning models should be combined so it is necessary to develop appropriate integration methods.

Assuming that the variables to be included in a synthetic fire risk index can be generated at the required temporal and spatial resolution, the most critical problem is to establish a coherent criterion to properly combine those variables. Since the goal is to obtain a single fire risk index, the component variables (vegetation, topography, climate, socioeconomic factors, *etc.*) should first be classified in a common numerical

scale of risk and then combined into a single index. In some cases, the proposal of risk levels implies changing the nominal-categorical scale of the original variables to an ordinal scale. On the other hand, the integration of the different components into a single risk index requires taking into account the relative importance on each factor in an specific area (*i.e.,* how much more importance has the human than the natural factors in the fire ignition probability?).

There are several methods for the integration of fire danger variables. Chuvieco *et al.* (2003) distinguish five groups of techniques for the integration of danger variables in a single fire danger index: (*i*) qualitative models, where arbitrary weights are based on the judgment of an expert; (*ii*) quantitative indices, based on multi-criteria evaluation; (*iii*) regression techniques, where statistical estimation methods are applied to explain fire occurrence; (*iv*) neural networks, similar conceptually to the regression model; and (*v*) physical models, based on meteorological conditions or on fire propagation models. In addition, probabilistic models can be used. These models show the advantage that (*i*) they deal with probability values, which are intrinsically normalised (0–1), and (*ii*) they are based in algebraic relationships such as Kolomogorov axioms and Bayes theorem. Probabilistic models have been widely used in ecological applications, for example, habitat modelling studies (Skidmore 1989; Fischer 1990; Aspinall 1992; Brzeziecki *et al.* 1993; Huntley *et al.* 1995) or population dynamic modelling (Soudant *et al.* 1997; Wilson *et al.* 2008; Renken and Mumby 2009).

Logistic regression analysis has been used widely both to predict and also to explain human- and/or lightning-caused fires by integrating geophysical, environmental, or socioeconomic variables (*e.g.,* related to topography, vegetation, land uses, climate and meteorological conditions, environmental parameters, fire danger indices, human factors) with observed fire occurrence (Martell *et al.* 1987; Vega-García *et al.* 1995; Lin 1999; Pew and Larsen 2001; Vasconcelos *et al.* 2001; Martínez *et al.* 2004; Wotton and Martell 2005; Kalabokidis *et al.* 2007; Prasad *et al.* 2008; Martínez *et al.* 2009; Modugno *et al.* 2008; Vilar *et al.* 2008; Nieto *et al.* 2006). Other statistical methods such as linear regression, classification regression trees, neural networks, generalized additive models, or Bayesian probability have also been used in fire risk mapping to generate risk models (Chuvieco *et al.* 1999; McKenzie *et al.* 2000; Sebastián *et al.* 2001; Chao-Chin 2002; Koutsias *et al.* 2004; Preisler *et al.* 2004; Robin *et al.* 2006; Amatulli *et al.* 2006, 2007; Amatulli and Camia 2007; Syphard *et al.* 2007; Vega-García 2007; Yang *et al.* 2007; Romero-Calcerrada *et al.* 2008).

Following Guisan and Zimmermann (2000), model development includes (*i*) the underlying of the conceptual model; (*ii*) the statistical formulation and the sampling design, where calibration and evaluation (= validation) datasets are also defined; (*iii*) the calibration of the model, where fitted values are obtained and tested for the quality of the fit; (*iv*) the calculation of predicted values using the model formulation and the validation dataset; and (*v*) the validation of the model using validation tables. Models are a representation of reality and, to ensure their accuracy, they should be tested and improved. Validation compares simulated system outputs with real system observations using data not used in model development (Mazzotti and Vinci 2007). According to Rykiel (1996), validation is a demonstration that a model, within its domain of applicability, possesses a satisfactory range of accuracy consistent with the intended application of the model. Validation therefore refers to model

performance. It describes a testing process on which to base on an opinion of how well a model performs so that a user can decide whether is acceptable for its intended purpose.

To validate the predictive power of a model two different approaches can be followed: (*i*) to use a single dataset to calibrate the model and then validate it by cross-validation, leave-one-out jack-knife or bootstrap methods and (*ii*) to use two independent datasets, one to calibrate the model and another one to validate it (Guisan and Zimmermann 2000). When using two independent datasets, any discrete measure of association between predicted and observed values can be used (*e.g.,* Fielding and Bell 1997; Stehman 1999; Guisan and Harrel 2000).

If the predictions of a statistical model are probabilistic, they need to be transformed back to the scale of the real observations. For binary data, it can be done by shortening probabilities at a given threshold (Guisan and Zimmermann 2000) and computing the omission and commission errors. One of the drawbacks of this approach is that one must select a threshold value, sometimes in an arbitrary way. Receiver Operating Characteristic (ROC) is a threshold independent measure that computes the model performance over all possible thresholds (Fawcett 2006). ROC is frequently used for the evaluation of species distribution models (Fielding and Bell 1997). It compares a rank map (*e.g.,* predicted probability) against a Boolean map (*e.g.,* fire presence/absence). ROC indicates how well the events of the Boolean map falls within the high suitability values in the rank map (Pontius *et al.* 2001).

Human, lightning, and integrated wildfire risk models have been validated using different approaches. Authors usually have randomly partitioned the sample and used one subset to fit the model and the other one to validate it (Sebastián *et al.* 2001; Vasconcelos *et al.* 2001; Vega-García 2007). Some authors used the ROC area under the curve (Modugno *et al.* 2008; Nieto *et al*. 2006) for validating. Other authors, however, employed residual analysis and Akaike Information Criterion (AIC), or the Hosmer and Lemeshow test to select the best model to fit the data (Yang *et al.* 2007). McKenzie *et al.* (2000) validated the model with standard diagnostics such as plot of residuals against fitted values and quantile-quantile plots. Also, they calculated a bootstrap estimate of prediction error for the regression models and compared it to the model's error sum of squares. Annual summaries of the modeled number of fires were compared to observations to examine the fit of the model in Wotton and Martell (2005). Amatulli *et al.* (2006) carried out a spatial validation in their fire risk resulting map from a CART model. They analyzed the correlation between the predicted fire risk value and the observed fire occurrence values. Also, they performed a second correlation analysis looking at the predicted and observed density values. The ignition points for validation falling in each fire management unit, expressed as observed density, were plotted against the predicted density values of the fire risk map. Dong *et al.* (2006) used linear regression to analyze the relationships between the value of area weighted of forest fire risk and the frequency of historical forest fires.

Short-term indices (fire danger rating systems) have been also validated, for example, Andrews *et al.* (2003) evaluated outputs of the U.S. National fire danger rating systems (US NFDRS) using logistic regressions and percentile comparisons, to examine the relationships between fire danger indices and fire activity. As independent variable in the logistic regression they used the indices (Energy Release

Component, Burning Index, Spread Component), whereas the dependent variables were fire-day, large fire-day, and multiple fire-day. Chuvieco *et al.* (2010) based the assessment of daily integrated indices on fire statistics (ignition points collected within 4 months of daily data), evaluating the existence of significant differences between the risk values of fire and no fire cells. They computed (*i*) the Mahalanobis Distance; (*ii*) the Mann-Whitney U-test; (*iii*) and the Nagelkerke R^2 coefficient from logistic regression fittings for each integrated index.

In the present study, two methods are proposed to integrate human- and lightning-caused wildfire probability models in the regions of Madrid and Aragón (Spain) at 1 km^2 grid cell resolution. The human and lightning individual models were generated in the context of the *Firemap* project (Chuvieco *et al.* 2010). Those models as well as the integrated ones have been validated by using wildfire occurrence data (x, y ignition points) as reported by official statistics and spanning the years 2005–2007.

METHODS

Study Areas

We selected two Mediterranean regions with different fire causality conditions in Spain: Aragón and Madrid. More than 90% of fires in the region of Madrid have a human cause and 10% are due to lightning. In the region of Aragón, the proportion of fires due to lightning rises to near 30%. The region of Madrid is located in central Spain and the region of Aragón in the North-East as shown in Figure 1.

The region of Madrid has 8028 km^2. It is composed of a mountain range that follows a NE-SW direction (with its highest peak having an elevation of 2428 m) and the Tagus river basin, which runs from the fault of the mountain range (800 m above mean sea level) to the Tagus' river bed (Fidalgo and Martín 2005). Madrid has Mediterranean climatic conditions but due to its altitude, the distance to the sea, and the barrier effect of the surrounding mountain ranges, it has a lower annual rainfall (300 to 1000 mm in the mountain range) and higher thermal amplitude than other Mediterranean regions. Pastures and shrub lands occupy vast areas in the region, whereas forest areas are mainly located in the mountain range, two-thirds of which are broadleaved woodlands. Holm oak (*Quercus ilex*), which is the predominant specie, can be commonly found in the typical Mediterranean *dehesa* formation, a sparsely meadow highly regarded from the point of view of its landscape as well as their recreational, environmental and livestock value. This region is the most populated in Spain, where urban areas have been increasing in size and population since the 1960s and spreading into agricultural and forest areas. Forest fires in Madrid are spatially associated with roads, railways, dump sites, and urban areas (Nicolás and Caballero 2001; Vilar *et al.* 2008). The contact boundary between urban and forest areas, which is commonly referred to as the Wildland–Urban Interface (WUI), is an area of major concern for regional fire managers. Regarding the known-cause fires in the last decade, about 80% of fires were due to human activities and only 3.64% of fires were due to lightning (MARM 2006).
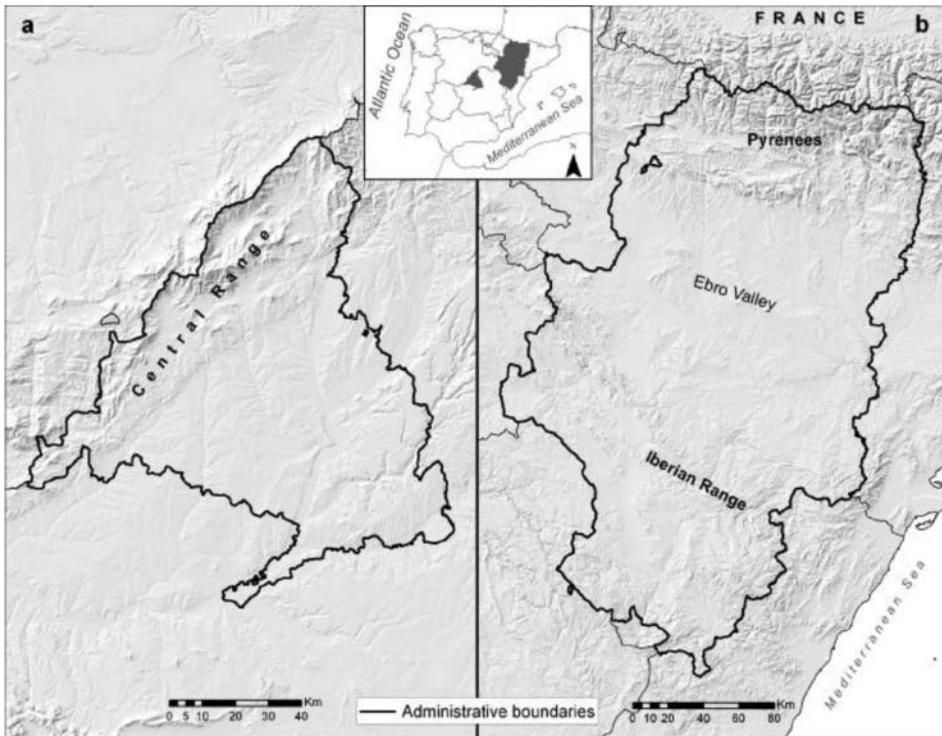
Figure 1. Study areas. The regions of Madrid (a) and Aragón (b) (Spain).

The region of Aragón has 47,500 km² distinguishing three geomorphologic units: the Pyrenees Range in the North, the Iberian Ranges extended at the South, and between them the Ebro Valley, a topographic depression crossed by the Ebro River. Due to its topographic characteristics it has a wide range of climatic conditions, from arid Mediterranean conditions in the valley to permanent snow in the highest peaks of the Pyrenees. In the central area (200 m above mean sea level) the annual precipitations is less than 400 mm with an annual average temperature around 14–15°C. In higher altitudes, in the mountains (600–1000 m above mean sea level) the average temperature is less than 10°C. In the Pyrenees Range the annual precipitations are around 1000–2000 mm while in the Iberian Range 1000 mm (Cuadrat 2004). Highest altitudes are mainly composed by natural vegetation (forest, shrub lands, and pastures) whereas the central depression is mainly composed by croplands. Dry mountainous areas are occupied primarily by conifer woodlands. In more humid areas, on the other hand, broadleaved species become dominant. In the Iberian Range (dryer conditions) conifer species are the most abundant (Gobierno de Aragón 1997). The human pressure has given to the territory a high level of landscape fragmentation, leaving few wildland areas especially in the poor and non-productive agricultural lands (Lasanta *et al.* 2006). The area of the Iberian Range is one of the lowest populated in Spain. In overall, the region of Aragón has one the lowest value of population density in Spain, 25 people by km². Regarding the wildfire cause typology in the last decade, without taking into account the fires
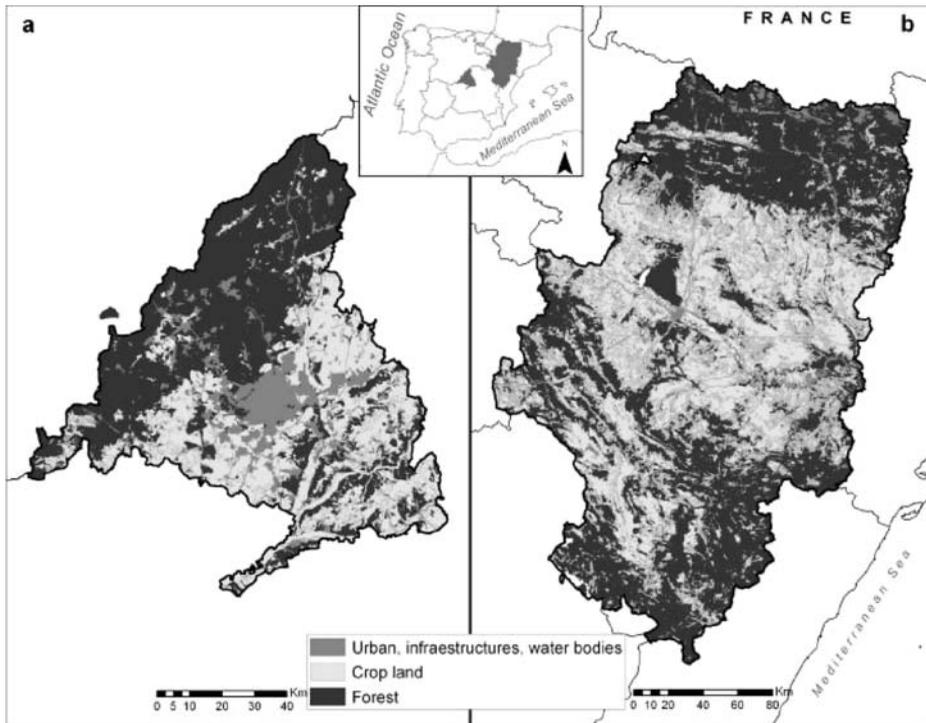
Figure 2. Main Land uses categories in Madrid (a) and Aragón (b) (*source*: Corine Land Cover 2000).

without a known reported cause, near a 30% of the fires were due to lightning. This region has the highest percentage of fires caused by lightning in Spain, due to its orographic and climatic conditions.

The main land uses in both study regions are shown in Figure 2. As we can see, forest areas in the study regions are mainly located in the mountain ranges. In the region of Madrid the urban areas are occupying big surfaces mainly located in the centre of the region. Croplands appears in the east and south areas, whereas in Aragón are occupying a large extension in the Ebro valley.

Data

Lightning- and human-caused wildfire probability of occurrence models

The probability of having at least one fire during the study period (3 years) for lightning- and human-caused wildfires has been obtained in the two study regions within the framework of the *Firemap* project. As previously mentioned more details on the fire risk scheme proposed in this project as well as on the methodologies applied to model the ignition potential from human and natural factors can be found in Chuvieco *et al.* (2010).

The lightning-caused models in the study regions were obtained by using 3 years of data (2002–2004) in a 3 × 3 km UTM grid. We were limited to this 3-year interval because of the availability of weather data required to build this model. In order to

Table 1. Results of lightning-caused wildfire probability models. Region of Madrid (a) and region of Aragón (b).

Variables	Description	B	Wald	Sig.	Exp(B)
a. Madrid					
Constant		−5.390	72.38	0.000	0.005
N Storms	Total number of thunderstorms	0.342	13.02	0.000	1.407
b. Aragón					
Constant		−7.344	155.17	0.000	0.001
N DMC Critical Days	Number of days in which the DMC is greater than a defined critical DMC threshold	0.007	25.19	0.000	1.008
N DryStorms	Total number of dry thunderstorms	0.144	69.63	0.026	1.155
% Conifers	% of conifers woodlands	0.007	4.94	0.000	1.007

evaluate if this period of time was representative enough of the mean conditions in the different areas regarding fire incidence, a U-Mann-Whitney test was applied to compare the average number of fires by day in this period (2002–2004) and recent historical data (1990–2001). We found that, at the 95% confidence level, there were no differences between the average number of fires per day during the study period versus the historical period. The independent variables used to build the models were those related to topography (*e.g.,* altitude, slope), vegetation (main forest cover types) and weather patterns represented by daily meteorological records (temperature, relative humidity, 24-h precipitation, wind speed), several codes that estimate the dead fuel moisture content from the National Fire Danger Rating System (NFDRS) and the Canadian Forest Fire Weather Index (CFFWI) and lightning data (number of strikes, intensity, number of thunderstorms).

The variables and descriptive statistics of the model are given in Table 1. The logistic regression results showed that the *number of thunderstorms* was the most significant variable in terms of probability of occurrence in both regions, achieving best results in Aragón by taking into account only the dry storms. Lightning-caused models for the two study areas are shown in Figure 3. Highest probability values are located over mountainous areas. The probability values range from 0.0046 to 0.2157 in Madrid and 0.0001 to 0.3883 in Aragón. More information about this model can be found in Nieto *et al.* (2006).

Logistic regression was also used to produce human-caused ignition probability maps at 1 km^2 grid cell resolution, using the 60% of the sample to fit the model and the remaining 40% to calibrate it. Independent variables used were those representing socioeconomic factors related to fire ignition (*e.g.,* roads, railways, recreational areas), which were obtained from diverse cartographic and statistical sources and mapped at 1 × 1 km grid cell resolution. This set of variables are expressed in density values and represents social factors related to human fire risk in Spain: socioeconomic changes, traditional activities in rural areas, accidents or negligence,
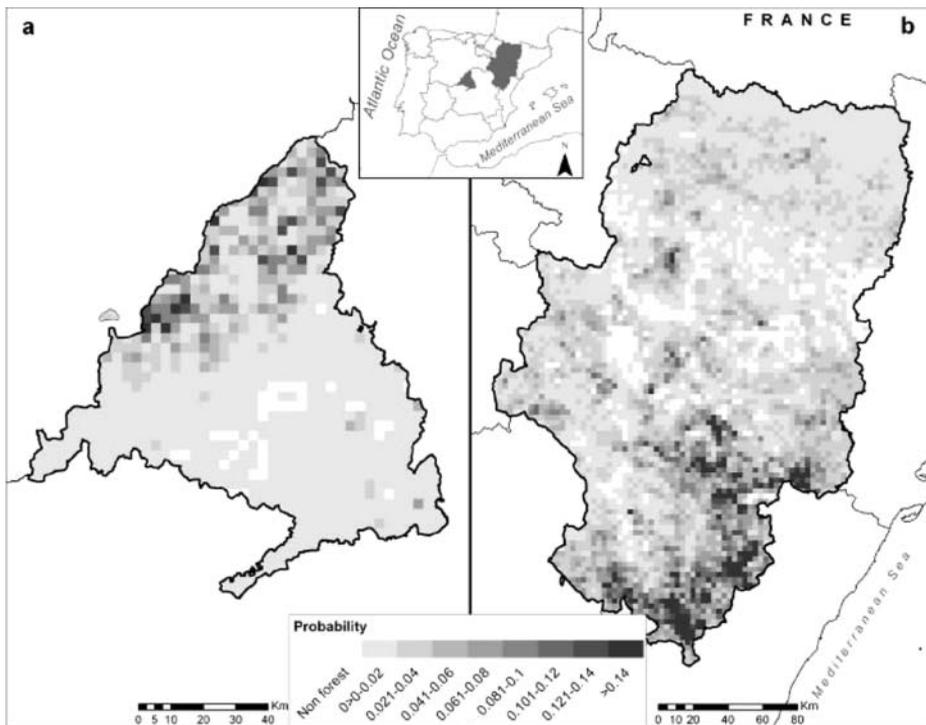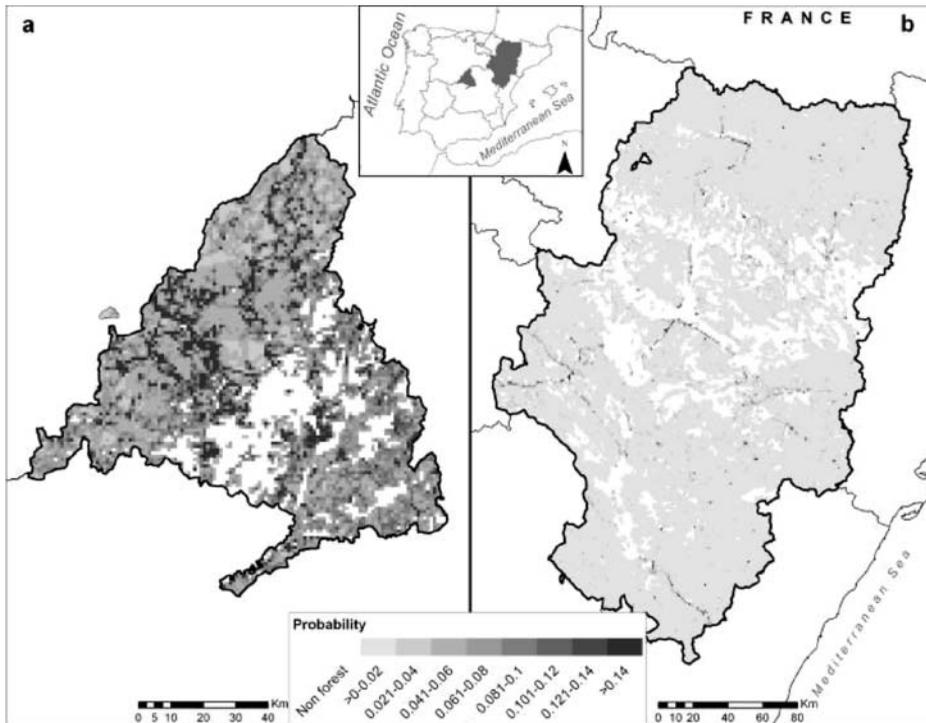
Figure 3.   Lightning-caused wildfire probability of occurrence maps. Region of Madrid (a) and region of Aragón (b).

fire prevention activities, and factors that can lead to social unrest (*e.g.,* land use disputes or high unemployment rates) (Martínez *et al.* 2009). Those factors have been reported by the literature and historical fire databases to have a direct or indirect influence in fire occurrence in Spain and could be considered representative of Euro-Mediterranean countries. The response variable used in the model were the fires due to human causes from 2002–2004 (x, y coordinates of the fire ignition points, as reported by the Fire Department in Madrid and from The National Fire records in Aragón). The logistic regression results showed that in Madrid the WUI that was included in the model as the area occupied by 1×1 km cell of the buffer of WUI (buffer size regarding the distance proposed by law of protection face to fire) was the most significant variable, along with the *roads in forest areas*. In Aragón, WUI was also selected by the model, followed by the *electric lines* variable, which represents the area occupied by 1×1 km cell of the buffer of electric lines, regarding the distance proposed by law of protection face to accidents. The obtained results, variables and descriptive statistics of the model, are given in Table 2. Human-caused probability maps for the two study areas are shown in Figure 4. The probability values range from 0.0385 to 0.7351 in Madrid and 0.00002 to 0.9527 in Aragón. From both lightning- and human-caused models non-forest areas were masked because we are considering only the probability of ignition of wildland fires, that is, those that occur in forest areas.

Table 2. Human-caused wildfire probability models. Region of Madrid (a) and region of Aragón (b). The units of the variables are density by 1 km² grid cell. The buffer distances have been established taking into account the legal protection area of each variable (*e.g.*, road category, railway, WUI).

		a. Madrid			
Variables	Description	B	Wald	Sig.	Exp(B)
Constant		−3.225	1020.985	0.000	0.040
Recreational area	Buffer of recreational areas	4.686	9.424	0.002	108.453
Road_b_for	Buffer of roadways in forest areas	9.657	21.095	0.000	15623.769
Trail_b_for	Buffer of trails in forest areas	0.941	9.442	0.002	2.561
Railway_b_for	Buffer of railways in forest areas	7.426	14.087	0.000	1678.899
WUI	Wildland Urban Interface	19.828	75.612	0.000	408633965.845
For_agricult_i	Forest-agricultural interface	1.472	31.821	0.000	4.356
Population_var	Variation of the population (1970–2004)	$0.0002 + E12$	5.608	0.018	1.000
	b. Aragón				
Constant		−5.672	992.840	0.000	0.003
Railway_b	Buffer of railways	7.470	46.585	0.000	1755.044
For_agricult_i	Forest-agricultural interface	1.857	60.837	0.000	6.406
WUI	Wildland Urban Interface	99.118	34.100	0.000	$1.113E + 043$
Public_mont	Public mountains	−0.957	11.009	0.001	0.384
Unemply_rate	Unemployment rate	0.035	6.570	0.010	1.036
Electric_line	Buffer of electric lines	84.680	47.612	0.000	$5 E + 036$
Extinction	Resources to extinct fire	1.558	12.789	0.000	4.748
Trail_b_for	Buffer of trails in forest areas	−0.672	7.849	0.005	0.511

349

**Figure 4.** Human-caused wildfire probability of occurrence maps. Region of Madrid (a) and region of Aragón (b).

Validation data: fire ignition points

In order to assess the temporal robustness of our models, an additional validation was performed with years excluded from the calibration period. Fire ignition points from 2005–2007 were used as an independent dataset to validate both the individual (human and lightning) and the integrated models in the two study areas. In the National Fire records database fire locations are referred to a 10×10 km grid and also at a municipality level. In recent years and depending on the region, the fire database has included the exact location (x, y coordinates) of the fire ignition points. In Madrid, the database including information on fire ignition coordinates provided by the Fire Department of the Madrid region contains a total of 728 fire ignition points during the chosen validation period (2005–2007). In Aragón, this database is provided by the National Fire records, and contains 1481 fire ignition points in 2005–2007. In Figure 5 are shown the spatial location of these points in the study areas.

Integration Methods

Since both models (lightning and human) have the same probabilistic scale (0–1) no transformation of the original values was needed prior to the integration. This integration has been performed following two different methodologies. (1) Probabilistic integration, based on Kolmogorov axioms (Tarantola 2005) and (2)
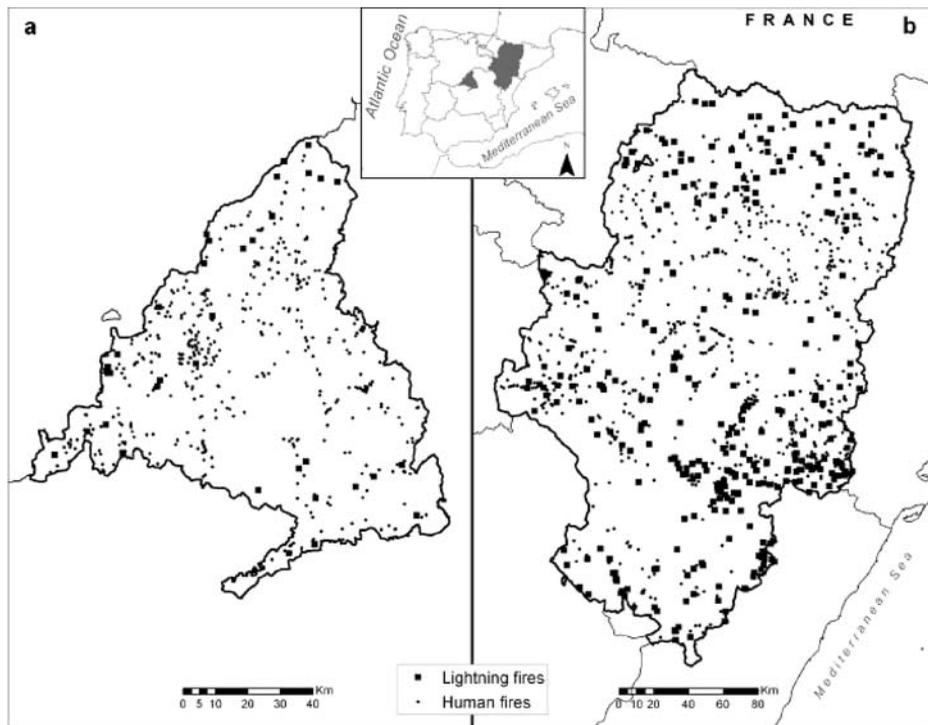
Figure 5. Fire ignition points for validation. Years 2005–2007. Region of Madrid (a) and region of Aragón (b).

average weighted by the historic occurrence of wildfires, meaning the proportion of fires due to human or lightning cause from the years 1990 to 2004 in each study area.

In the probabilistic approach, we assume that the integrated probability of the occurrence model should explain the probability of occurrence of either of a human-caused or a lightning-caused fire. Based on the Kolmogorov axioms, the integrated probability of occurrence can be expressed following the addition law of probability:

$$P(A \cup B) = P(A) + P(B) - P(A \cap B) \tag{1}$$

where $P(A \cup B)$ is the integrated probability, $P(A)$ and $P(B)$ are the probability of both events (human- and lightning-caused fires) and $P(A \cap B)$ is the probability that both lightning and human fires will happen. Eq. (1) can be simplified into Eq. (2), assuming that lightning-caused and human-caused fires are independent events at the grid resolution and when a long enough period of time is consider

$$P(A \cup B) = P(A) + P(B) - P(A)P(B) \tag{2}$$

The second integration approach is based on a weighted average of the probability of occurrence of lightning- and human-caused fires. The weights are based on the proportion of human and lightning of fires from historic records from 1990–2004 (National Fire records source) and is expressed as:

$$[P(A) \times \text{historic human - caused fire occurrence}] + [P(B) \tag{3}$$
$$\times \text{historic lightning - caused fire occurrence}]$$

where P (A) is the probability of human-caused fires and P (B) is the probability of lightning-caused fires. The historic fire occurrence of human or lightning fire causes is expressed in terms of proportion of fires due to human or lightning cause by grid cell in the period 1990–2004.

Validation

To carry out the validation of the lightning- and human-caused models as well as the integrated ones we count on the fire ignition points (x, y coordinates) from 2005–2007 in each region as mentioned before. First of all, in order to validate the lightning- and human-caused models separately, the validation data (fire ignition points) were classified by human or lightning cause. In Madrid there were 557 fires due to human causes (94%) and 35 due to lightning (6%) in the validation period, while in Aragón the figures were 690 (68%) and 321 (31%), respectively. To validate the resulting integrated models we used the total set of fire ignition points (excluding unknown causes). The total ignitions in Madrid were 592 and 1011 in Aragón. We evaluated the existence of significant differences between the predicted fire occurrence probability values on fire and no-fire cells (Chuvieco *et al.* 2010). To evaluate these differences we used Receiver Operating Characteristic (ROC) analysis (Fawcett 2006) and Mahalanobis Distance (Mahalanobis 1936). In ROC analysis the Area Under the Curve (AUC) represents the probability that the assay result for a randomly chosen positive case (fire) will exceed the result for a randomly chosen negative case (no fire). AUC is the portion of the area of the unit square, its value will always be between 0 and 1.0. However, because random guessing produces the diagonal line between (0.0) and (1.0), which has an area of 0.5, no realistic classifier should have an AUC less than 0.5 (Fawcett 2006). Then, an AUC with a 0.5 value means non-discrimination; between 0.5–0.69 a poor discrimination; 0.7–0.79 reasonable; 0.8–0.89 excellent; 0.9 or higher exceptional (SPSS 2006). The asymptotic significance was set to less than 0.05, which means that using the assay is better than guessing.

Mahalanobis Distance is based on correlations between variables by which different patterns can be identified and analysed. It is widely used in cluster analysis and in other classification techniques. Formally, the Mahalanobis Distance from a group of values with mean $\mu = (\mu_1, \mu_2, \mu_3, \ldots, \mu_N)^T$ and covariance matrix S for a multivariate vector $x = (x_1, x_2, x_3, \ldots, x_N)^T$ is defined as:

$$MDx = \sqrt{(x - \mu)^T S^{-1}(x - \mu)} \tag{4}$$

From Viegas *et al.* (1999) and Andrews *et al.* (2003), the Mahalanobis Distance is expressed as

$$MD = [(X_1 - X_2)/\sigma]^2 \tag{5}$$

where X is the probability value from the integrated results, X_1 is the average of the probability values on no-fire cells, X_2 is the average of the probability values on fire cells, and σ is the standard deviation of the probability values on all cells.
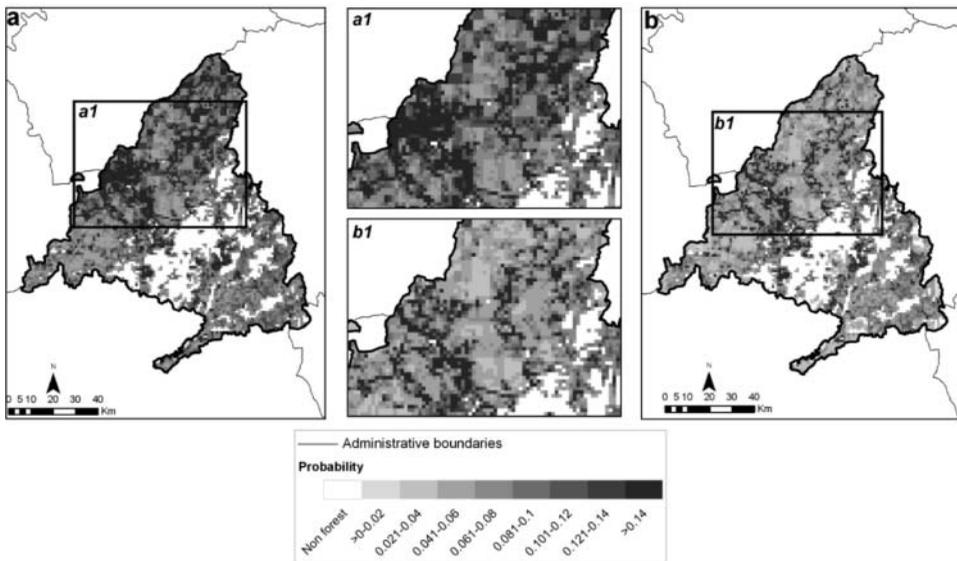
Figure 6.   Integration probability models in the region of Madrid: Kolmogorov probabilistic integration (a), weighted by the historic fire occurrence average of human- and lightning-caused integration (b).

RESULTS

Integration of Lightning- and Human-Caused Models at 1 × 1 km Grid Cell Resolution

The results from the probabilistic and the weighted integration for Madrid are shown in Figure 6. Both integration methods show the same pattern in the spatial distribution of probability values. The highest values are located to the west, south-east, and following the northern direction in the central range. Cells with higher probability values follow the roads and areas with high density of *WUI*. The human component dominates the integrated results in this region, which is in accordance with historical fire causes (Figure 4a). In north areas that belong to the central range, probability values are related to the lightning-caused model, which enhances the integrated result. In areas where the lightning-caused probability values are low, it is the human model that is influencing the final result (east and south-eastern areas). Regarding the differences between the two maps, the probability values obtained by probabilistic methodology are higher than the ones from the weighted average probability method.

The integration results in Aragón are shown in Figure 7. The spatial distribution of the probability values shows similar trends using the two integration methods. The highest values are located in the southeast (Iberian range). This probability distribution is in accordance with the lightning-caused model (Figure 3b), where the highest probability values were located in the Iberian range. However, high probability values from the human-caused model (*e.g.,* cells following WUI or electric lines located in north, center, and west areas of the region) are also included in the integrated result (Figure 7). As in the region of Madrid, the probability values of
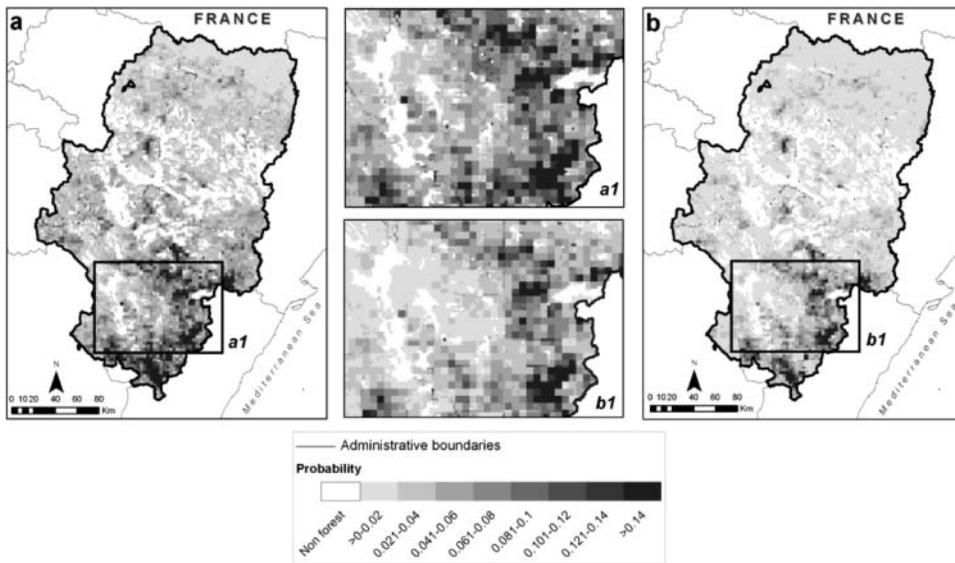
Figure 7. Integration probability models in the region of Aragón: Kolmogorov probabilistic integration (a), weighted by the historic fire occurrence average of human- and lightning-caused integration (b).

the integrated maps using the probabilistic method are higher than those obtained with the weighted average. The areas with higher values are located at the southeast of the region.

Given in Table 3 are the descriptive statistics for the two methods used in the integration for all the cells in the study region as well as in cells with and without fire. In the region of Madrid, the probabilistic method and weighted average show maximum probability values of 0.737 and 0.735, respectively. The probabilistic integration method presents a higher mean probability value (0.104) than the weighted average method (0.075). In the cells with no fire the values are mostly the same as in the all sample. In those cells with an observed fire the mean values are higher for the probabilistic (0.141) than for the weighted integration method (0.111). In the region of Aragón, the probabilistic method shows higher maximum values (0.952) than the weighted average (0.886). The average value is lower with the weighted average method (0.024) than with the probabilistic integration method, which shows an average value of 0.044. In the no-fire set, the values are quite similar to the ones in the whole dataset. In those cells where a fire has been observed, the mean values of probability obtained in both methods are higher than in cells without a fire. In both regions, the highest variability in the integrated probability is obtained using the weighted average (variation coefficients of 125% and 73% for Aragón and Madrid, respectively).

Validation

We carried out the validation of the lightning- and human-caused models as well as the two integrated models at 1×1 km grid cell resolution. In Figure 8 is

Table 3. Descriptive statistics the integrated models: probabilistic, weighted average and single average in the region of Madrid (a); and in the region of Aragón (b) at 1 × 1 km grid cell resolution.
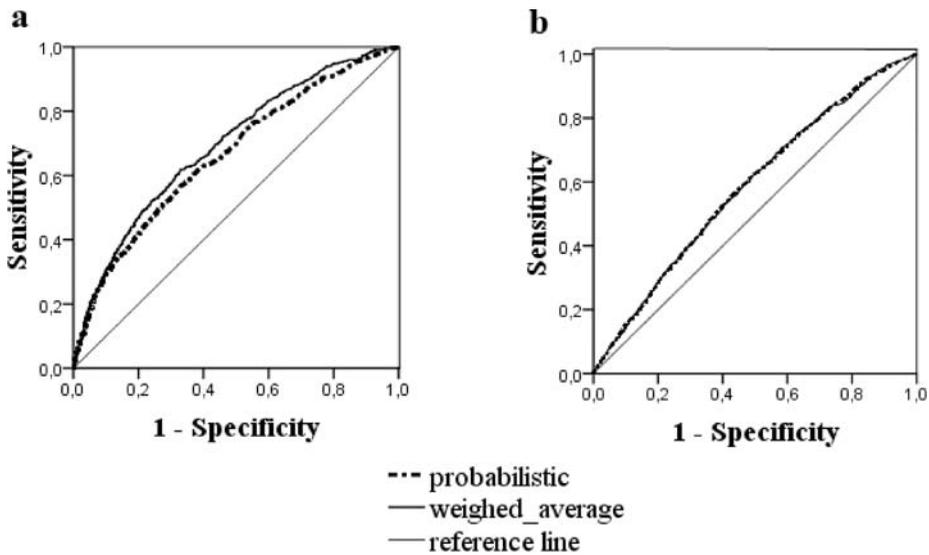
a. Madrid

	N	Minimum	Maximum	Mean	Std. deviation	Coefficient of variation
Total						
Probabilistic	7052	0.043	0.737	0.104	0.062	60%
Weighted average	7052	0.004	0.735	0.075	0.055	73%
Cells without fire						
Probabilistic	6467	0.043	0.737	0.100	0.058	58%
Weighted average	6467	0.004	0.735	0.072	0.051	71%
Cells with fire						
Probabilistic	585	0.043	0.686	0.141	0.092	65%
Weighted average	585	0.022	0.627	0.111	0.082	74%

b. Aragón

	N	Minimum	Maximum	Mean	Std. deviation	Coefficient of variation
Total						
Probabilistic	39842	0.000	0.952	0.044	0.041	93%
Weighted average	39842	0.000	0.886	0.024	0.030	125%
Cells without fire						
Probabilistic	38797	0.000	0.952	0.043	0.041	95%
Weighted average	38797	0.000	0.886	0.024	0.030	125%
Cells with fire						
Probabilistic	1045	0.002	0.602	0.054	0.051	94%
Weighted average	1045	0.001	0.333	0.031	0.036	116%
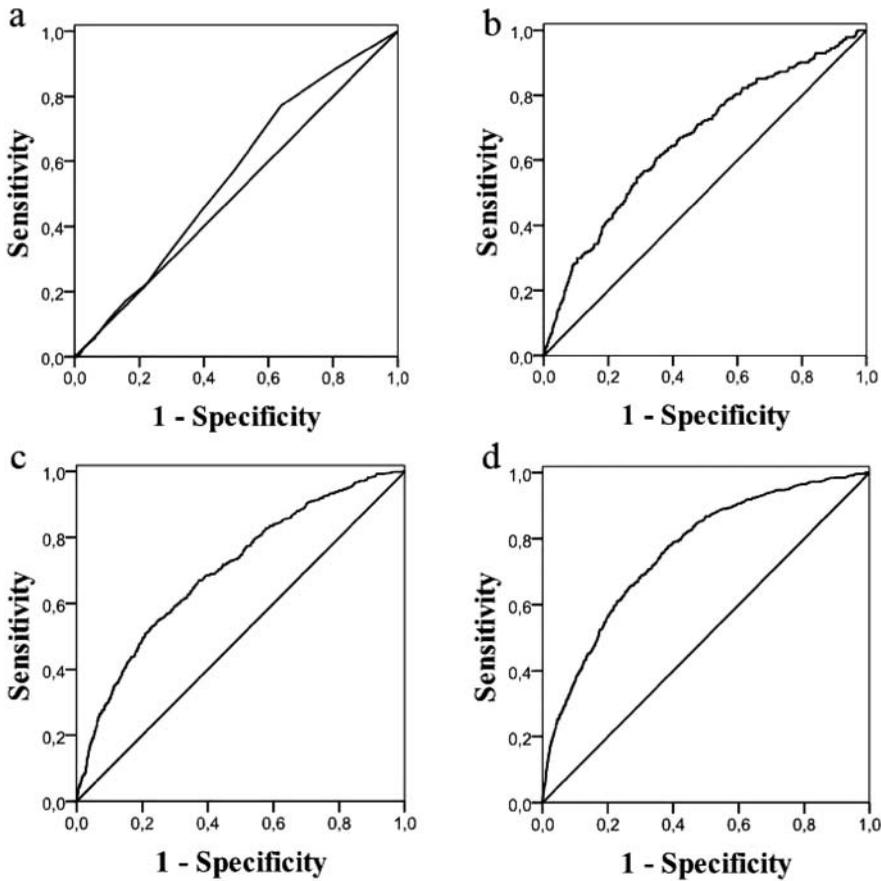
Figure 8. ROC for the lightning-caused probability of occurrence fire models in Madrid (a) and Aragón (b); ROC for the human-caused probability of occurrence fire models in Madrid (c) and Aragón (d) at 1×1 km grid cell resolution.

shown the ROC curve obtained for the individual models in the two study regions. In Madrid the lightning ROC curve presents a segmented shape. In Aragón, the human-caused model presents a regular ROC curve similar to the one from the lightning-caused model but with lower values. The ROC for the integrated-caused probability models is shown in Figure 9. In Madrid the resulting curve for the weighted average probability values presents higher values than the curve from the probabilistic method whereas in Aragón, the curves from the two methods have similar values. The values of the AUC for the human- and lightning-caused models as well as the integrated results are given in Table 4. In Madrid, the AUC for the lightning- and human-caused model is 0.553 and 0.702, respectively, which means that for the human model the classification is reasonable whereas is not satisfactory for the lightning model. The AUC for the probabilistic is 0.662, whereas the AUC for the weighted average method is slightly higher (0.693), showing that both integration methods improve the performance of the lightning model but it

Figure 9. ROC for the integrated probability methods in the study areas: Madrid (a) and Aragón (b).

worsen the results for the human model. In Aragón the AUC for the lightning- and human-caused model is 0.663 and 0.762, respectively. Again the human model performs better than the lightning one. However, these values decrease to 0.585 for probabilistic integration and 0.584 for the weighted average, meaning that the integration is practically useless.

Regarding Mahalanobis Distance results in Madrid, the weighted average shows the highest value (0.490) that is in accordance with the obtained AUCs. In this region, the weighted average presents the highest difference between the probability in the fire and no-fire cells. In Aragón, the probabilistic method presents the highest value (0.067). It means that, in the probabilistic integration method, the probability of cells with and without fire differs more than when using the weighted average method. Shown in Table 5 are the Mahalanobis Distance results.

DISCUSSION

The spatial distribution of the probabilities of wildfire occurrence is almost the same for the two integration methods, varying only their values ranges. Comparing the integrated results with the original maps (lightning- and human-caused maps) we find that in Aragón the integrated results are dominated by the lightning-caused wildfire model, while in Madrid by the human-caused model. However, in Aragón, cells where the human-caused model presents high values enrich the integrated probability results. In the region of Madrid, we find that the lightning-caused model is influencing the final result in north areas, where there have been high probability values coming from this model. This behavior is in accordance with the historical causality of fires in both regions: the majority of fires in Madrid are human-caused (∼90%), whereas in Aragón, the causality of lightning fires is

358

Table 4. Area Under the Curve, standard error, *p*-value and 95% confidence interval for the lightning- and human-caused probability of occurrence models and integrated models at 1×1 km grid cell resolution in Madrid (a) and Aragón (b).

				Asymptotic 95% confidence interval	
Model	Area	Std. error[a]	Asymptotic sig.[b]	Upper bound	Lower bound
a. Madrid					
Lightning-caused	0.553	0.044	0.278	0.466	0.640
Human-caused	0.702	0.012	0.000	0.680	0.725
Probabilistic	0.662	0.012	0.000	0.639	0.686
Weighted average	0.693	0.011	0.000	0.671	0.715
b. Aragón					
Lightning-caused	0.663	0.016	0.000	0.632	0.694
Human-caused	0.762	0.009	0.000	0.745	0.780
Probabilistic	0.585	0.009	0.000	0.568	0.602
Weighted average	0.584	0.009	0.000	0.567	0.601

[a]Under the nonparametric assumption.
[b]Null hypothesis: true area = 0.5.

Table 5.   Mahalanobis Distance.

	a. Madrid
Model	Mahalanobis Distance
Probabilistic	0.435
Weighted average	0.490
	b. Aragón
Probabilistic	0.067
Weighted average	0.052

more important, representing the ~30% of total reported fires. The descriptive statistic showed that the weighted average integration has a higher variability of values than the probabilistic integration approach, and therefore it seems that this approach has a better capability of representing the different factors affecting ignition.

Regarding the validation of the obtained results using the independent ignition points sample from 2005–2007, in both study areas the original human-caused probability model reaches a reasonable discrimination by using ROC (~0.7). The lightning-caused models showed a poorer performance, being almost satisfactory in the region of Aragón (0.66) but not getting a significant discrimination in the region of Madrid (0.55). Related to the integrated results, in the region of Aragón the discrimination is not satisfactory, while in the region of Madrid it reaches a better discrimination only when using the weighted probability. However, this integration method takes into account the past fires, which may nuance the probability results because the fire trends could change. In this area only the human-caused model reaches a reasonable discrimination. The results of the Mahalanobis Distance agree with the ROC validation, where significant highest distances are found when using the weighted average in Madrid. Comparing the obtained results with related works we find that AUC values in the region of Madrid are close to those from Modugno *et al.* (2008) in their human-caused models (~0.7). No similar works have been found to compare with the lightning model.

In the region of Aragón the human-caused model has been obtained using a small number of fire ignition points as dependent variable. This was due to the location errors that were found in the original dataset. This may be causing an underestimation of the wildfire occurrence due to human causes. Also, in Aragón there are more fires due to lightning than in the region of Madrid. In this region the lightning-caused model hardly ever influences the final integrated result (except for north areas of the Central range), due to its low probability values. Indeed, the integrated model performs similarly but poorer than the human model alone due to the influence of the lightning model. We have compared these results with the ones obtained at a coarser scale, 3×3 km grid cell resolution. Lightning- and human-caused models at this resolution have been integrated following the probabilistic and the weighted average methods. Then, they have been validated by using ROC and Mahalanobis Distance. The obtained AUC follow the same trends as in the

previous scale but with higher values, meaning that the models perform better at a coarser resolution.

At 3 × 3 km grid cell resolution the human-caused and the weighted average integrated models obtain the higher AUC values, being for the integrated model 0.719 in Madrid and 0.639 in Aragón. This better fit indicates that the change in the scale is affecting the results. With a coarser scale the uncertainty in the fire ignition spatial location clearly decreases. In addition, the individual models have been calibrated only with 3 years of fire data, due to restrictions imposed by the availability of meteorological data (from 2002 to 2004), and this may be influencing in the final result (Nieto *et al.* 2006). This fact is particularly important in the case of the lightning model, since this model includes meteorological data that can be very variable through the years.

As more data become available the fitting and validation of the individual models could be improved as well as the integrated results. In addition, a longer time-series of fire data should be required to improve independent validation and assessment of results. Integration results are poor as they are expected to improve individual models performance but this is only achieved for the lightning model and even in this case the validation results are still not satisfactory. In spite of that, the integration alternatives proposed are an objective method to weight the variables (human and lightning causative agents) according to its relative importance on fire occurrence.

CONCLUSIONS

We have tested two methods (probabilistic and a weighted average) for the integration of lightning and human fire caused models at 1 × 1 km grid cell resolution. Two different geographic regions regarding fire causality were compared to get a better performance assessment of both methodologies. The proposed methods show a lower accuracy than the original lightning- or human-caused models used to obtain the integrated results in the region of Aragón or than the human-caused model in the region of Madrid. The use of a weighted average by the historic fire occurrence fits better in Madrid. In the region of Aragón the obtained fit is not satisfactory. Regarding the spatial distribution of the integrated fire risk, it corresponds with the spatial distribution of the phenomenon related to the fire causes of each region. Validation is an essential step to test the sustainability of the predicted results and if their accuracy is consistent for the application of the model. Validation results in Madrid show that some improvements in the individual models are necessary to reach a satisfactory level of the estimation in the integrated models. In Aragón, models would require a revision of original data, especially the response variable. Despite of the effort we made to integrate the ignition fire models due to human and lightning causes, better original fire data should lead to better models and conclusions. The spatial inaccuracy of fire statistics may be having a critical effect in the final results. As we have tested, the integrated models improve their performance at a coarser scale. Also, when a longer time series data become available these results could be improved.

Long-term fire risk indices require the integration of fire ignition components (human and lightning). Those components have different impacts on fire risk

conditions. Identifying which are more relevant and how they should be weighted to generate synthetic indices is a critical phase in risk assessment for fire prevention and mitigation management. The results obtained in this work show that proposed methods can be considered as an alternative to integrate the information of causative agents in order to estimate fire ignition probability. However, further assessment is required in other periods and regions to check consistency and generalization potential.

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