Research Article

Modelling Fire Ignition Probability from Satellite Estimates of Live Fuel Moisture Content

Sara Jurdao [1,*], Emilio Chuvieco [1], and Jorge M. Arevalillo [2]

[1] Department of Geography, University of Alcalá,
Calle Colegios 2, 28801, Alcalá de Henares, Spain

[2] Department of Statistics, Operational Research and Numerical Analysis,
National University of Distance Education,
Pº Senda del Rey 9, 28040, Madrid, Spain

*Corresponding author: Tel.: 34-91-885-5257; e-mail: sara.jurdao@uah.es

ABSTRACT

Biomass burning has critical ecological and social impacts. Recent changes in climate patterns and land use have involved alterations of traditional fire regimes, which have increased the negative impacts of fire. Live Fuel Moisture Content (LFMC) has proven to be one of the main factors related to fire risk, as it affects fire ignition and fire behavior, and therefore it is an essential indicator for fire risk assessment. The aim of our research was to explore several methods to convert LFMC into Ignition Probability (IP) at a national scale, considering climate and vegetation functional types. The project covers the Iberian Peninsula territory of Spain (492 175 km^2), for a ten year period. The LFMC data was estimated from NOAA-AVHRR imagery, whereas fire occurrence was based on the standard MODIS Thermal Anomalies product (MOD14). Non-parametric significance tests, histograms and percentiles, classification trees, and logistic regression models were used for estimating the IP from five variables based on LFMC. These modelling approaches were compared and Logistic Regression (LR) analysis was found to be most advantageous, since it uses several predictor variables to compute a continuous probability of IP. The area under the ROC curve of the LR models for the Iberian Peninsula was 0.65 for the Mediterranean region and >0.8 for the Eurosiberian region. The LFMC from one week before the fire detection was the most influential variable in the statistical analysis and it was the main variable in the Mediterranean models. In the Eurosiberian models, the LFMC decrement since spring was also important. The LFMC one week before the fire detection and the difference between the LFMC one week and two weeks before the fire detection were included in the grassland model. Shrubland is less susceptible to rapid moisture changes than grassland, so the LFMC from two weeks before the fire and the LFMC decrement since spring were more influential.

Keywords: fires, Iberian Peninsula, Ignition Probability, Live Fuel Moisture Content, logistic regression, MODIS, Spain

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INTRODUCTION

Biomass burning has a great influence on vegetation disturbance and succession, as well as on worldwide greenhouse gas emissions (Goetz *et al*. 2006, van der Werf *et al*. 2006, Chuvieco 2008). During recent years, severe fire seasons have been observed in several countries (Portugal, 2005; Greece, 2007; Australia, 2009; Russia, 2010; and others), due to climatic factors, such as heat waves or precipitation disturbances, and as a result of changes in land use derived from socio-economic trends (Martínez *et al*. 2009). For this reason, there is a growing emphasis on improving fire risk assessment systems, which predict when and where a fire is more prone to ignite or where it may cause more negative impacts (Chuvieco *et al*. 2010). Fire risk indices include different variables, such as weather conditions, topography (mainly slope gradient), fuel amount and geometric characteristics, and socio-economic conditions (Preisler *et al*. 2009). One of the main factors required to improve those fire risk indices is a more accurate estimate of the fuel moisture content (FMC), since this is closely related to fire ignition and fire propagation (Nelson 2001). In Spain, 96.1 % of all fires are human caused (Área de Defensa contra Incendios Forestales 2006). Fires caused by lightning are also very relevant (Vilar *et al*. 2010) as such fires tend to burn large areas because of their isolated locations and difficult accessibilities, and because they are characterized by simultaneous multiple ignitions (Wotton and Martell 2005). Since plants constitute the main ignition material in a forest, their moisture content plays an important role because it may serve to retard ignition or mitigate propagation of a fire. Fuels with high moisture content need higher temperatures or longer periods of heat exposure to ignite, because the heat is required for evaporation, leaving less energy available to initiate combustion (Dimitrakopoulos and Papaioannou 2001). In addition, fire propagates slower in wet fuels than in dry fuels as the evaporated fuel moisture inhibits combustion by diluting the flammable gases in the reaction zone and cooling the flames (Albini 1976, Shafizadeh *et al*. 1977). For this reason, the FMC is a common component of fire danger assessments (Blackmarr and Flanner 1968, Fosberg and Schroeder 1971).

The FMC is commonly expressed as the amount of water per dry mass of the fuel (Lawson and Hawkes 1989). It is defined by the expression,

$$FMC = \left(\frac{W_w - W_d}{W_d} \right) \times 100 \, , \tag{1}$$

where W_w and W_d are the wet and dry weights of a sample unit. The dry weight is usually obtained after oven drying the sample at 60 °C for either 24 h or 48 h (Viegas *et al*. 1992).

When considering FMC, a distinction between dead and live fuels should be made as their FMC varies according to different factors. Dead fuels are closely affected by weather and environmental conditions, while the live fuels are also influenced by soil moisture (which in turn is determined by weather variability) and the ecophysiological characteristics of each species (Camia *et al*. 2003). Hence, since species have diverse mechanisms to survive summer drought, each can have a different live FMC for the same weather conditions.

The FMC can be estimated from field work, but this process is laborious and costly. For this reason, most operational estimates of FMC, particularly for dead fuels, are based on meteorological indices (Simard 1968, Finney 1998, Aguado *et al*. 2007). These methods require spatial interpolation to obtain complete spatial coverage. Due to the fact that live fuels are associated with more than weather conditions, alternative methods based on satellite images have been used to estimate FMC of live fuels (LFMC). These methods can be divided in two large groups, depending on whether they use empirical or simulation models. The former rely on statistical fittings between satellite derived indices and field measurements, and therefore are site-specific, but can be extended to areas with similar conditions (Chuvieco *et al*. 2004*b*, García *et al*. 2008). The simulation models are based on radiative transfer equations and try to account for the impact of water content on plant reflectance at different wavelengths. These methods can be generalized to larger areas although their parametrization is more complex than empirical fittings (Ceccato 2001, Yebra *et al*. 2008*a*).

To include LFMC information into fire risk assessment systems, one should translate the original scale of LFMC values (percentage of dry weight) into a risk scale that can be combined with other factors of fire ignition or propagation. The former is commonly approached by transforming LFMC values into ignition probability (IP; Chuvieco *et al*. 2004*a*), defined as the likelihood that the fuel would ignite when exposed to a heat source. Several papers have presented methods to derive IP from LFMC data. They can be classified in two broad approaches: (1) studies based on biophysical parameters derived from experiment results such as subjecting fresh foliage to flammability tests in order to investigate its ignitability; or (2) studies based on relating moisture values to historical fire occurrence. Within the first group, most of the studies have attempted to establish a critical LFMC threshold below which the fire IP would increase significantly. A clear example of this approach is Rothermel's (1972) concept of moisture of extinction (ME), defined as the moisture threshold above which fire cannot be sustained. Albini (1976) estimated the ME for grassland at 40 %, and Trabaud (1976) found a similar ignition threshold for Mediterranean maquis at 45 %. For several Mediterranean shrubs, this threshold was established at 105 % by Dimitrakopoulos and Papaioannou (2001). Using this critical ME threshold, Chuvieco *et al.* (2004*a*) estimated IP from LFMC, based on an inverse linear relation between ME and the actual LFMC value (the closer to the ME, the lower the IP). The second approach to establish critical thresholds of LFMC to define IP has been based on analyzing statistical relations between LFMC and fire occurrence. Dennison *et al.* (2008) found for chaparral ecosystems (shrubland plant community in California), that large fires (>1000 ha) only occurred when LFMC was less than 77 %, although most of the large fires occurred when LFMC was below 71 %. Afterwards, the same authors developed a new analysis by increasing the sample size and including antecedent precipitation patterns. Their conclusion was that 79 % LFMC was the threshold strongly related to large fires (Dennison and Moritz 2009). This result was similar to that obtained by Schoenberg *et al.* (2003), who found that chaparral burned area increased below an LFMC threshold of 90 %. Pellizzaro *et al.* (2007) observed that most of the fires in several Mediterranean shrublands of Italy occurred with LFMC values below 100 %. Other authors propose using a gradual scale that correlates the IP increment to the LFMC decrement. For example, Green (1981) established three fire intensity classes in chaparral ecosystems, with the highest intensity occurring below 60 % LFMC. Weise *et al.* (1998) considered four fire danger classes in which fire danger was also extreme below 60 % LFMC. Consequently, IP is defined by a statistical tool like histograms and percentiles. More recently, logistic regression (LR) models were used to estimate IP in Mediterranean grasses and shrubs (Chuvieco *et al*. 2009), while Dimitrakopoulos *et al.* (2010) have used classification trees to explore multiple factors associated with IP.

Since these empirical approaches were based on local historical fire data, they are difficult to extrapolate to other areas. This paper follows an empirical method, but tries to extend the models to a larger territory, which includes a variety of climatic and vegetation conditions. Our aim is to present the results of generating IP values based on LFMC estimates using a variety of modelling methods.

METHODS

Input Data Description

This study covers the whole Iberian Peninsula territory (492 175 km^2), which is one of the most fire-affected areas in Europe (Martínez *et al*. 2009). The time series under analysis spans from 2001 to 2007. To obtain statistical models between fire occurrence and LFMC, two sets of data were derived: the LFMC was based on empirical models applied to satellite images, while the fire occurrence was estimated from the MODIS Thermal Anomalies product (MOD14).

The LFMC data was produced by García *et al.* (2008) and it has been calculated from 1998 to 2012 using empirical models based on extensive field measurements of LFMC. The product is based on 8-day composites performed with 8 daily NOAA Advanced Very High Resolution Radiometer (AVHRR) images, at 1 km^2 spatial resolution. Due to the physiological differences between grasslands and shrubs, a different model for each vegetation type was fitted using multivariate linear regression. The models were based on three input variables: the Normalized Difference Vegetation Index (an estimator of vegetation chlorophyll activity); surface temperature data (which is associated with evapotranspiration); and a harmonic function of the day of the year (accounting for seasonal trends). The first two variables were derived from 8-day maximum brightness temperature value composites. In order to include the interannual variations in LFMC seasonal trends, the third input variable was adjusted depending on whether the fire year was dry or wet at the beginning of the spring season. This consideration took into account the Cumulative Water Balance Index (CWBI) for measuring regional drought stress (Dennison and Roberts 2003) and an estimate of the soil water reservoir (Gandullo 1994). The years with negative values of CWBI and no soil water reservoir were classified as dry years. Consequently, a different function of the day of the year was fitted for each type of year (dry or wet) and for each vegetation type (grassland and shrubland). The resulting models provided a mean error of 42.1 % for grasslands and 14.2 % for shrublands. More information about this product is described in García *et al*. (2008). We include here an example of a LFMC 8-day composite (Figure 1).

The LFMC greatly varies between species depending on their physiological strategies to regulate water content (Pellizaro *et al.* 2007). Further, these strategies are highly related to local climate conditions. Therefore, we built our models based on vegetation functional types and climate strata. The selected LFMC product was developed just for grassland and shrubland so these were the two vegetation groups we analyzed (Figure 2). The vegetation types were derived from the Corine Land Cover 2000 map (http://www.eea.europa.eu/data-and-maps/data#c12=corine+land+cover+version+13, last accessed November 2011) but the woodland category was not included in our analysis. The climate regions considered were Eurosiberian or Mediterranean biomes (Figure 3), which were extracted from a biogeographical classification developed by Rivas Martínez (1983). In order to distinguish between the regions, the Rivas Martínez (1983) classification system was based on the potential evapotranspiration of the summer months and also on the average precipitation for the same period of time. In general terms, the Mediterranean region included the areas where the evapotranspiration was higher than the precipitation. Further, the Mediterranean areas show more contrast between maximum and minimum temperatures and less precipitation than the Eurosiberian areas, so the Mediterranean areas are distinguished by a marked drought in summer. Ecophysiological studies have investigated how the climate may have contributed to

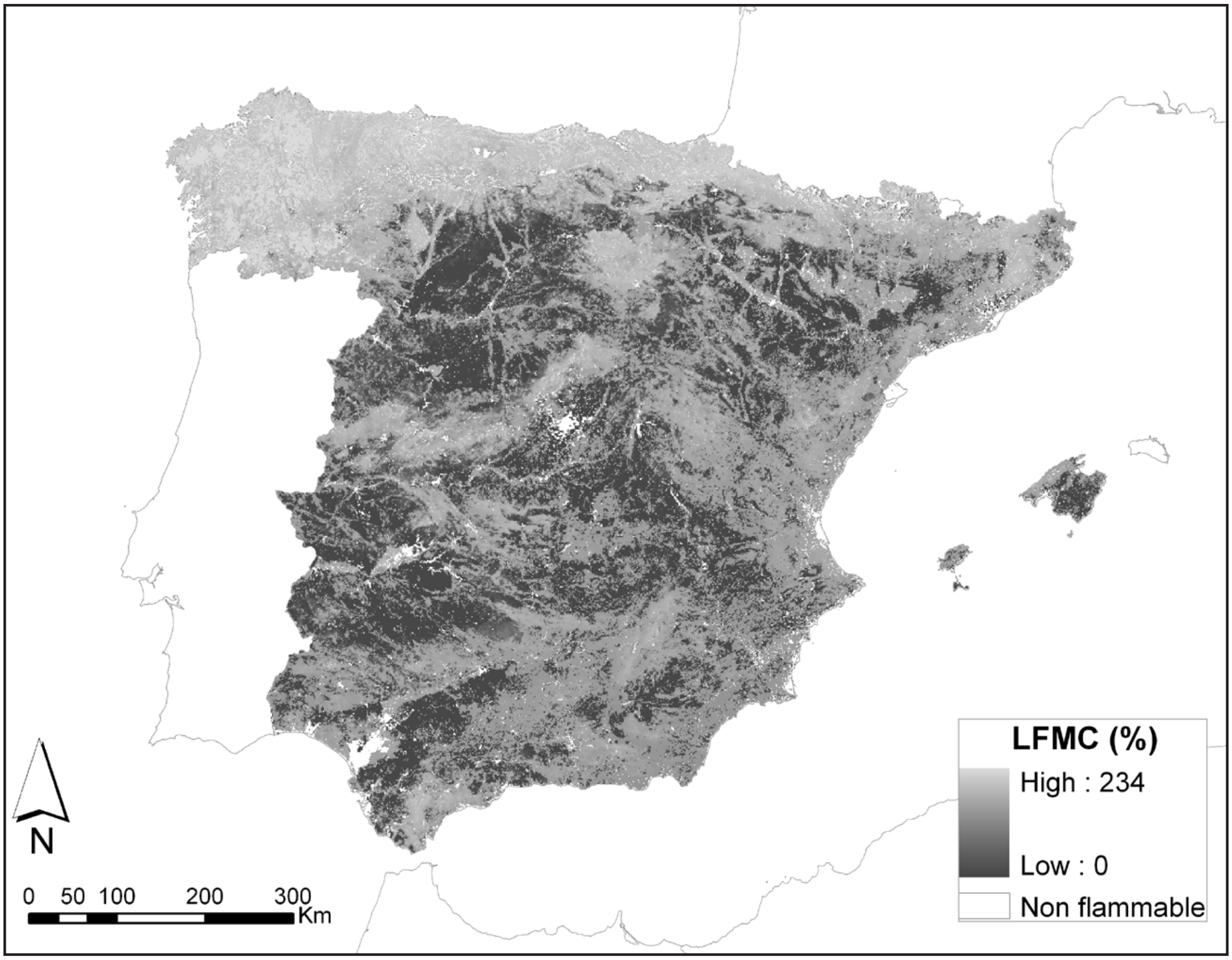

Figure 1. Example of a LFMC map from 5 to 12 of August 2007. The product was computed from 8 daily NOAA-AVHRR images at 1 km² spatial resolution. Empirical models for grassland and shrubland were developed by García *et al.* (2008).

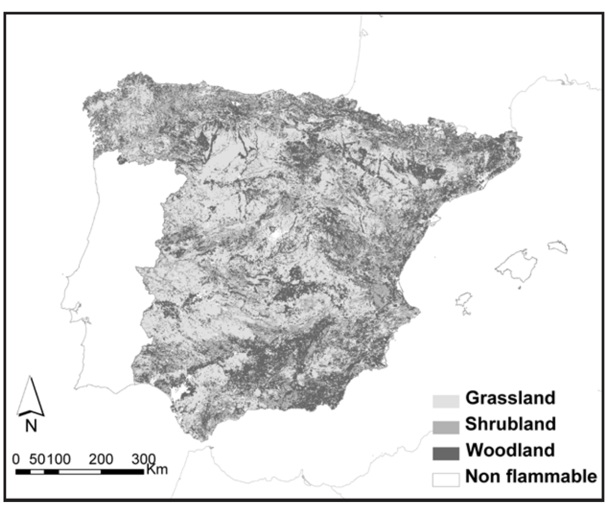

Figure 2. Vegetation stratification according to the Corine Land Cover 2000 reclassification.

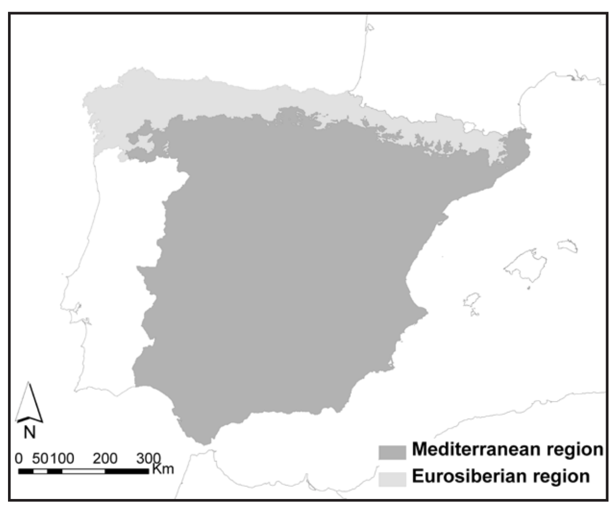

Figure 3. Biogeographical stratification according to Rivas Martínez (1983).

shape vegetation distribution (Moreno *et al.* 1990). In this sense, in the Mediterranean region, vegetation is well adapted to summer drought but highly dependent on the availability of water and nutrients during spring and autumn in order to compensate for the reduction in photosynthesis activity caused by the greater summer stress (Tenhunen *et al*. 1987). Typical vegetation from this region is: *Quercus ilex* L., *Cistus ladanifer* L., *Rosmarinus officinalis* L., *Erica australis* L. and *Phillyrea angustifolia* L. (Rivas Martínez 1987). The vegetation encountered in the Eurosiberian region is more sensitive to the climate of the dry period and to temperature in the coldest season (Moreno *et al*. 1990) and as representative examples we find *Quercus robur* L. and *Fagus sylvatica* L. as deciduous trees, and also *Betula celtibérica* Rothm. & Vasc. and *Buxus sempervirens* L. (Rivas Martinez 1982). Plant nomenclature follows Lopez-Gonzalez (1994).

In summary, the stratification groups that were tested for the statistical modelling of IP from LFMC data were: (1) fire and non-fire pixels in grasslands and shrublands, and (2) fire and non-fire pixels in four climate-vegetation models: Mediterranean grasslands (MG), Eurosiberian grasslands (EG), Mediterranean shrublands (MS), and Eurosiberian shrublands (ES). An additional stratification was performed for the descriptive analysis based on the seasonality of moisture conditions. In Mediterranean climates, LFMC typically reaches its highest value at the end of spring and then decreases during summer and autumn until precipitation returns in late autumn or winter (Chuvieco *et al*. 2004*b*). Therefore, we considered three temporal stages: grasslands and shrublands in spring (30 March to 17 June), grasslands and shrublands in early summer (18 June to 28 August) and grasslands and shrublands in late summer (29 August to 31 October).

Regarding fire occurrence, we tried to use official fire statistics for Spain, but they do not have precise UTM (Universal Transverse Mercator) coordinates of ignition points. The fires are georeferenced to a 10 km × 10 km UTM grid net (http://www.marm.es/es/biodiversidad/temas/defensa-contra-incendios-forestales/estadisticas-de-incendios-forestales/default.aspx, last accessed February 2012). Since the LFMC data has a 1 km^2 resolution, we considered that the official fire statistics may be affected by spatial interpolation methods, and decided to use MODIS Thermal Anomalies product (MOD14) as a surrogate of fire occurrence. Previous studies have shown that MOD14 correlates well to fire occurrence (Hawbaker *et al*. 2008), especially for large fires (Oliva *et al*. 2008, Morato 2009). Therefore, fire occurrence was selected from the MOD14 product. The detection algorithm identifies pixels, at 1 km^2 spatial resolution, in which one or more fires are actively burning at the time of the satellite overpass (Giglio *et al*. 2003). The results are hotspots shown as the centroids of the pixels. Our temporal series of analysis started in 2001 because it was the year in which MOD14 was available. Data were downloaded from the University of Maryland's fire research group (http://maps.geog.umd.edu, last accessed February 2012). Only those hotspots with a confidence level higher than 80 % were selected for this analysis to avoid commission errors related to agricultural burns, high temperature soils, and specular surfaces. We had a total of 3874 and 2305 fire pixels for grassland and shrubland, respectively.

Selection of Non-Fire Pixels

The statistical models of LFMC and fire occurrence required defining a sample of areas not affected by fires. Those areas were selected from cells surrounding hotspots. For that, the semivariogram geostatistical technique was computed for each spatial and temporal stratification unit to find out the threshold distance at which the spatial autocorrelation in LFMC was significantly reduced (known as the sill). The outputs of the semivariogram study showed that the sill was reached at approximately 10 km. Then, a first buffer around each fire pixel was established at this distance, to avoid selecting non-fire pixels contaminated by actual burns. The width of the sampling area was established at 10 km in order to keep the same ecological characteristics of the vegetation of the areas affected by fires, especially for the Mediterranean region, which can be very heterogeneous. Then, 700 non-fire pixels were extracted for each stratification unit from inside both circular rings (Figure 4). This number was determined according to Fink (1995) and Bartlett *et al*. (2001) to get a representative number of samples for the models. Sample sizes of 69 198 and 36 945 non-fire pixels were selected for grassland and shrubland, respectively. This approach facilitated enough variability outside of the fire pixels, while keeping similar ecological conditions to those pixels affected by the fire. As shown in Figure 5, some buffers were incomplete since only shrublands and grasslands were considered in our analysis. In addition, in order to ensure that any fire pixel was not selected as a non-fire pixel, the area in a 1 km buffer was removed around hotspots with all confidence levels

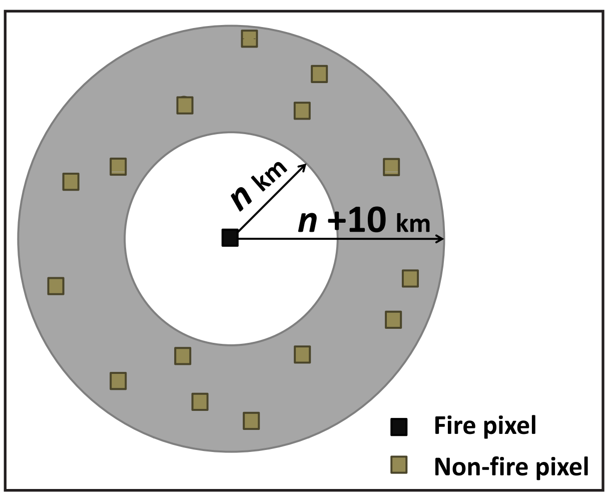

Figure 4. Example of a fire pixel and its corresponding buffer where the non-fire pixels are randomly selected with *n* representing the range obtained by the semivariograms.

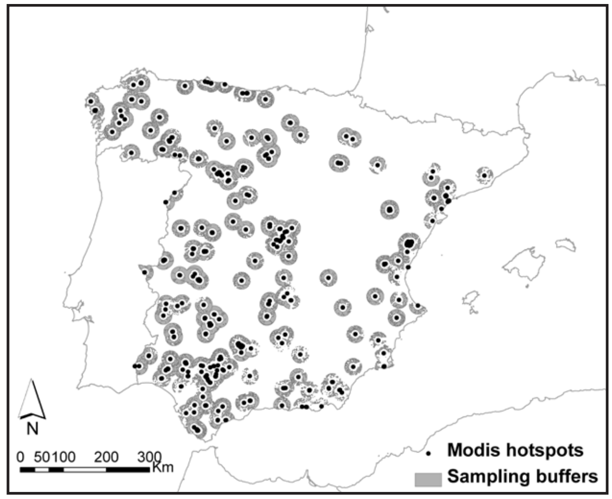

Figure 5. MODIS hotspots for the year 2007. Shown are the centroids of pixels where thermal anomalies were detected at 1 km^2 spatial resolution, with a detection confidence that estimates its quality (low-confidence fire, medium-confidence fire, or high-confidence fire). For the present analysis, only those hotspots with a high-confidence level (>80 %) were selected. Also represented are the buffers where the non-fire spots were selected.

Statistical analyses

The predictive potential of LFMC to estimate fire occurrence was tested by selecting LFMC values from several 8-day periods (Table 1) before the fire detection as independent variables ($LFMC_{t-n,}$ where n = 1 to 5). Using non-parametric statistics, only LFMC values from one and two periods before the fire ($LFMC_{t-1}$ and $LFMC_{t-2}$) were found significant (P < 0.001) to discriminate fire and non-fire pixels. The 8-day period including the date of the fire ($LFMC_t$) was not considered for the statistical analysis, as we tried to obtain a predictive model.

In addition to the mentioned two variables, the following temporal indices were tested as explanatory variables:

$$Difference = LFMC_{t\text{-}1} - LFMC_{t\text{-}2} \quad (2)$$

$$Slope = \frac{LFMC_{t-1} - LFMC_{\max spring}}{tLFMC_{t-1} - tLFMC_{\max spring}} \quad (3)$$

Table 1. Description of the independent variables used to predict fire occurrence. LFMC = Live Fuel Moisture Content and IP = Ignition Probability.

Variable	Description	Rationale
$LFMC_{t-1}$	LFMC corresponding to the 8-day period prior to the period including the fire date.	The lower the LFMC is one or two weeks before the fire detection, the higher IP is expected.
$LFMC_{t-2}$	LFMC corresponding to the 8-day period prior to $LFMC_{t-1}$.	
Difference	Moisture variation between two previous periods to the fire date.	The more the moisture decreases before the fire detection, the higher IP is expected.
Slope	Moisture gradient between the maximum LFMC value and the period before the fire date.	The larger the moisture decrease is with respect to the maximum LFMC spring record for the same temporal and spatial placement, the higher IP is expected.
Anomaly	Departure of LFMC values before the fire date from the average value of that period during the time series.	The lower LFMC is recorded before the fire detection comparing to the mean recorded for the rest of the years, the higher IP is expected.

where $LFMC_{\max\ spring}$ is the maximum LFMC found in the spring season in the year of analysis, and $tLFMC_{t-1}$ and $tLFMC_{\max\ spring}$ are the dates of the $LFMC_{t-1}$ composite and of the $LFMC_{\max\ spring}$ composite, respectively.

$$Anomaly = \left(\frac{LFMC_{t-1}}{meanLFMC_{t-1}}\right) \times 100, \qquad (4)$$

where $meanLFMC_{t-1}$ is the average $LFMC_{t-1}$ value computed for the same pixel and date as $LFMC_{t-1}$ in all the years considered in the analysis, not including the actual year of analysis.

The non-parametric U-Mann-Whitney test for differences was used to test whether the explanatory variables showed statistical significance between fire and non-fire pixels, as a first test to select the most significant variables for the predictive models. To build these models, three methodologies were used: (1) histogram thresholding based on percentiles; (2) classification trees; and (3) logistic regression analysis.

The histogram thresholding is a simple method based on the frequency distribution of a selected variable. In this case, we computed the proportion of fire pixels that occurred at certain LFMC percentiles. Then, an IP to each percentile was assigned and the ninetieth and tenth percentiles were selected as critical thresholds to extract the lowest and highest IP, respectively. This criterion to set up relevant thresholds for IP determination was used by other authors to determine fire danger levels (Andrews *et al*. 2003). De Groot *et al*. (2005) used a similar approach to analyze the relationship between the Fine Fuel Moisture Code (FFMC) of the Canadian Fire Weather Index System and MODIS hotspots in Africa.

The classification tree analysis was performed with the CART algorithm (Breiman *et al*. 1984). This algorithm recursively splits the input database (fire or non-fire samples) using binary rules described by optimal cut-offs, which should be highly correlated to the binary output. The tree growing process is carried out in a recursive way until a large tree structure is obtained. Then, an automated optimal pruning of such structure is carried out by removing uninformative branches to avoid overfitting. The resulting model is a tradeoff between predictive accuracy and tree complexity. The splits can be obtained using impurity measures, such as Gini, entropy, towing, etc., which provide criteria to determine the optimal selection. Each branch is created to maximize the homogeneity of the descendant nodes (the maximum heterogeneity would be a branch with the same number of fire and non-fire pixels). The CART decision tree models provide rich information for estimating the IP at the terminal nodes of the trees. Such estimates can be obtained from the Bayes rule that gives the posterior probabilities of fire and non-fire at a terminal node *t* by:

$$P(1\,|\,t) = \frac{\pi_1 \times \frac{N_1(t)}{N_1}}{P(t)}, P(2\,|\,t) = \frac{\pi_2 \times \frac{N_2(t)}{N_2}}{P(t)}, \quad (5)$$

with $$P(t) = \pi_1 \times \frac{N_1(t)}{N_1} + \pi_2 \times \frac{N_2(t)}{N_2}, \quad (6)$$

where $P(1\backslash t)$ and $P(2\backslash t)$ are the posterior probabilities of non-fire or fire, N_1 and N_2 are the number of non-fires and fires in the dataset and $N_1(t)$ and $N_2(t)$ are the number of non-fire and fire pixels at the terminal node t of the tree. In addition, π_1 and π_2 are the prior probabilities for both categories of the outcome variable. Further theoretical details concerning the CART algorithm are described in Breiman *et al*. (1984).

For this study, all the trees were grown using optimal parameters provided by the CART algorithm, and the input data were divided in two subsets with 60% for learning and 40% for testing the tree models. The Gini splitting rule was selected for all of the spatial units under study. In addition, we carried out several trials that showed that a parameterization with $\pi_1 = \pi_2 = 0.5$ was the best choice. The resulting classification tree models were assessed using the Area Under the Curve (AUC) obtained by the Receiver Operating Characteristic (ROC) plot method (Fielding and Bell 1997).

The third method for modelling IP in this study was logistic regression (LR). In order to test the consistency of the explanatory variables and to select the most relevant ones, we chose the Forward Wald method. Then, the independent variables were entered in the model in an additive way, resulting in a linear equation (Equation 7). This equation is included in the computation of *P* (Equation 8), which stands for the probability of fire.

$$z = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots\ldots\ldots + \beta_r x_r \quad (7)$$

$$P = \left(\frac{1}{1+e^{-z}}\right) \quad (8)$$

The equation coefficients were calculated via the maximum likelihood method, and the IP for each record in the database can be estimated by means of Equation 8. In addition, LR also provides significance levels for testing the null hypothesis $\beta_i = 0$, where $i = 0, 1, \ldots r$, which are useful to quantify the importance of each independent variable in the model. The results were also assessed using the AUC of the ROC. All the statistical tests were performed with SPSS v15.0 (SPSS 2006).

RESULTS

Testing for Differences

Significant differences between fire and non-fire pixels were observed for most of the independent LFMC variables at the majority of the spatial and temporal units, with $LFMC_{t\text{-}1}$ and $LFMC_{t\text{-}2}$ being the most significant variables (Figure 6). The $LFMC_{t\text{-}1}$ showed the highest significance in all scenarios, with the exception of early summer where $LFMC_{t\text{-}2}$ became more relevant. Anomaly was significant for grassland, especially in the Eurosiberian region where drier periods would lead to a considerable LFMC decrease. Slope was not found to be significant in spring for shrubland,

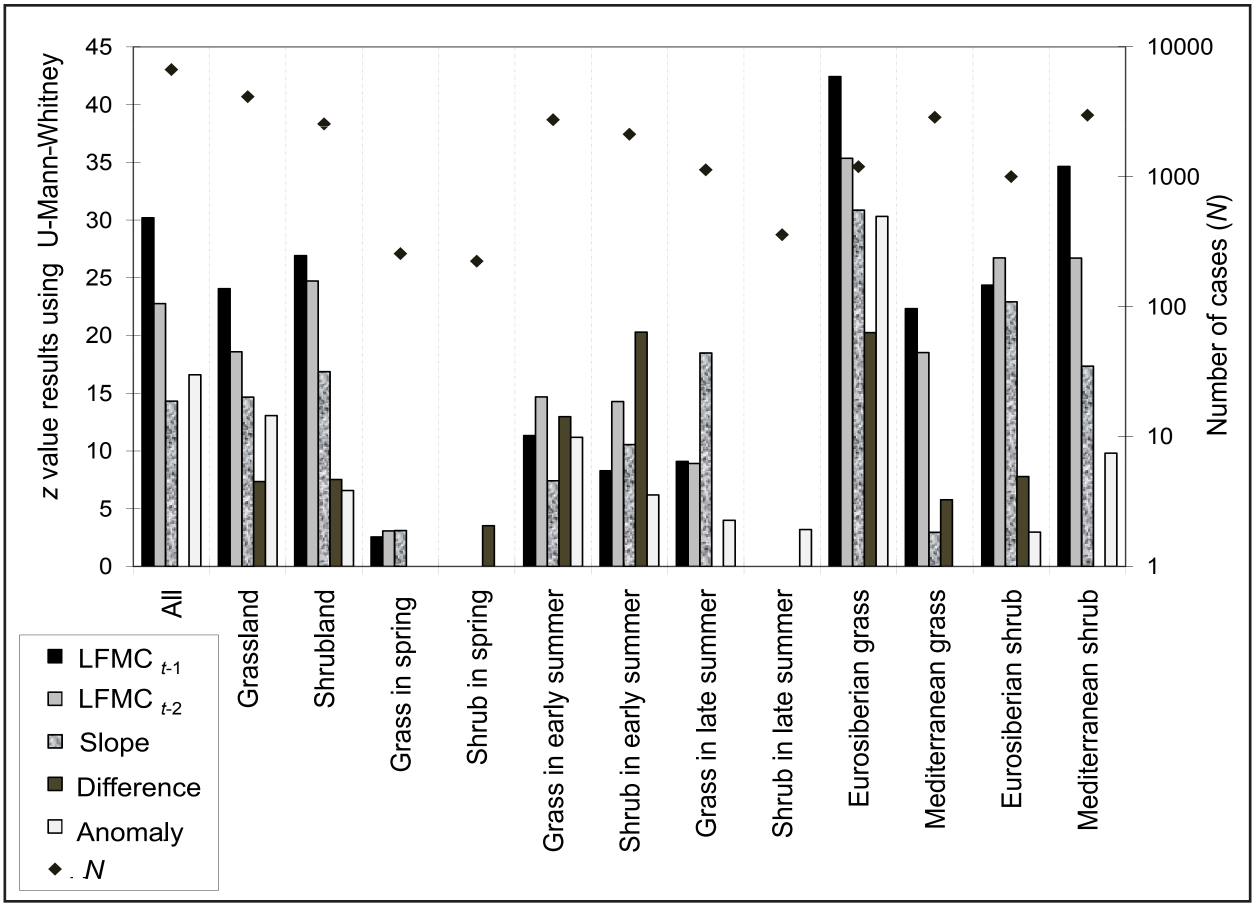

Figure 6. *z* values using U-Mann-Whitney test for the variables that show significant differences between fire and non-fire areas (α = 0.01). Most of the independent LFMC variables showed significant differences between fire and non-fire pixels, the $LFMC_{t-1}$ and $LFMC_{t-2}$ being the most significant.

but it showed high *z* values on grassland in late summer when this vegetation type exhibits lower LFMC values. It is worth noting that there are fewer significant variables for the spring time period than in summer.

Histograms and Percentiles

We selected $LFMC_{t-1}$ for this analysis as it showed the highest significance in the U-Mann-Whitney test. For fires occurring on shrubland, most of the hotspots had a $LFMC_{t-1}$ lower than 100 %, with a peak close to 80 % (Figure 7). Above $LFMC_{t-1}$ of 140 %, few hotspots were observed (9.53 %). For grassland, most fire pixels had $LFMC_{t-1}$ values below 40 %. However, some anomalously high $LFMC_{t-1}$ values were found for some fire pixels (>120 %).

Non-fire pixels and fire pixels exhibited different distributions across the $LFMC_{t-1}$ intervals (Figure 8). Non-fire pixels were represented proportional to the occurrence of $LFMC_{t-1}$ intervals but the curve for fire pixels displayed a sharp fall, which indicated more fires at low values of $LFMC_{t-1}$.

According to the results provided by the percentiles (Figure 9), 50 % of fires occur when $LFMC_{t-1}$ was below 25.76 % for grassland and below 79.95 % for shrubland. The $LFMC_{t-1}$ critical value for 90 % of fire occurrence was 127.12 % for grassland and 105.51 % for shrubland. These values were 1.35 % and 57.79 %, respectively, for the tenth percentile

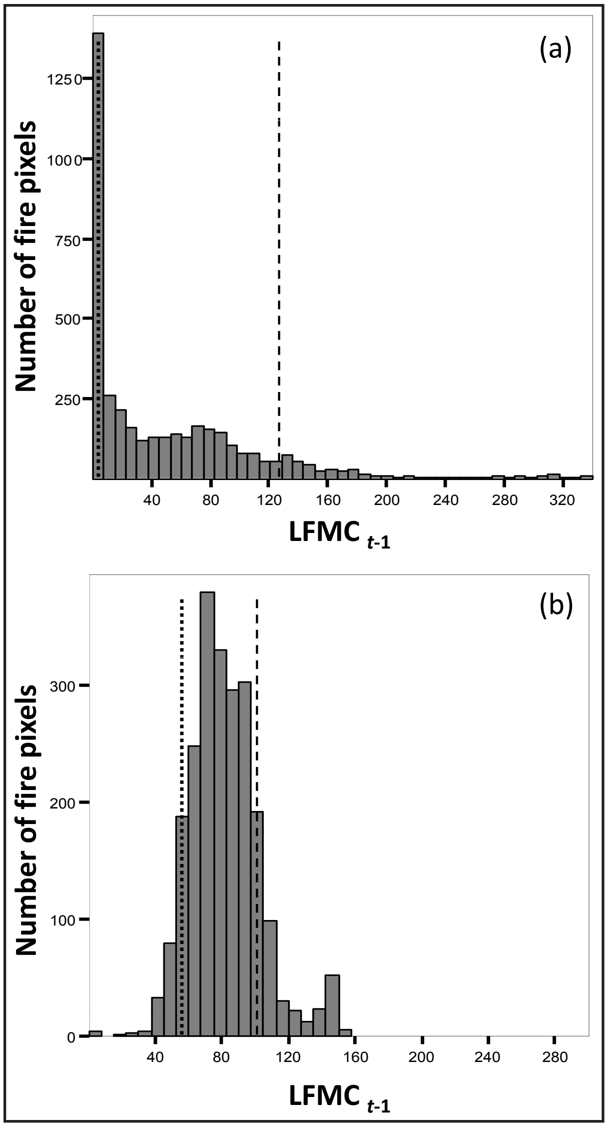

Figure 7. Frequency distribution of $LFMC_{t-1}$ for grassland fire pixels (a) and shrubland fire pixels (b). Dotted line refers to the tenth percentile while dashed line refers to ninetieth percentile. Most of the hotspots had an $LFMC_{t-1}$ lower than 100% for shrubland and lower than 40% for grassland.

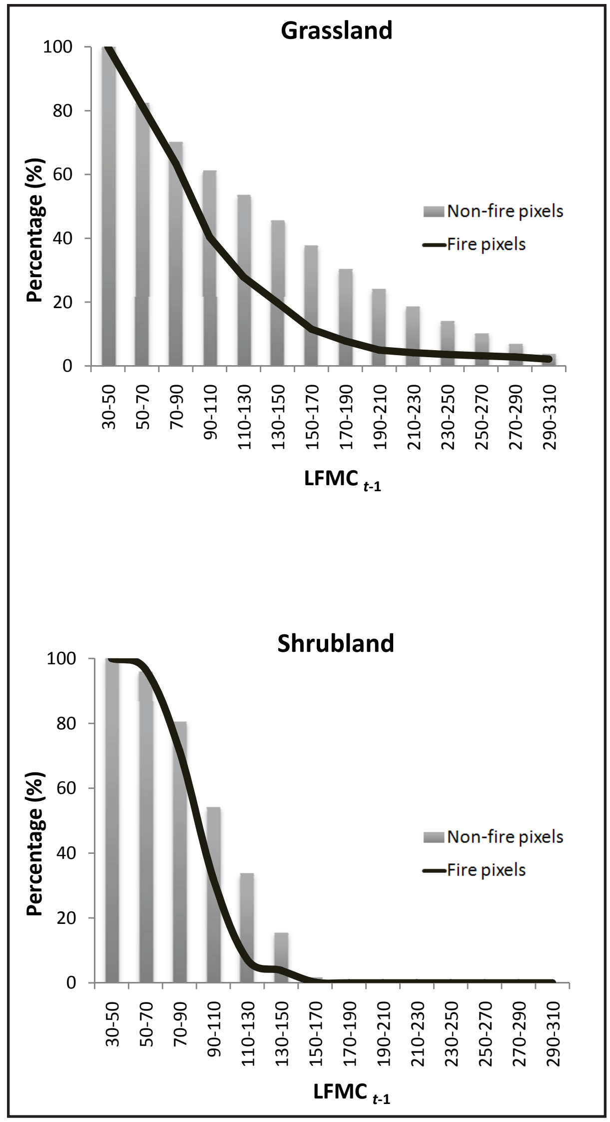

Figure 8. Percentage of fire pixels and non-fire pixels above a certain $LFMC_{t-1}$ interval showing that for higher $LFMC_{t-1}$ the presence of fire pixels is lower than the presence of non-fire pixels.

of fire occurrence. An IP was assigned to each percentile, with the highest IPs corresponding to the lowest percentiles, and vice versa. Note that a conservative value of 10% was established as the lowest IP.

Classification Tree Modelling

The CART models generated after stratifying by vegetation groups alone did not show significant information, so this analysis combined climate zones and vegetation types in four sampling units: MG, EG, MS, and ES (Figure 10). The tree structures provided by the figure correspond to the data of the sampled pixels.

Note that in all cases, the first splitting variable was $LFMC_{t-1}$, which confirmed the importance of this variable to estimate fire occurrence. Additionally, the slope variable was found relevant to estimating fire occurrence in the ES and MG models.

Percentiles	Grassland LFMC $_{t-1}$	Shrubland LFMC $_{t-1}$
100	340	152.22
90	**127.12**	**105.51**
80	88.65	96.47
70	70.36	91.12
60	48.04	85.5
50	25.76	79.95
40	12.27	74.57
30	2.3	70.79
20	1.35	65.17
10	1.35	57.79

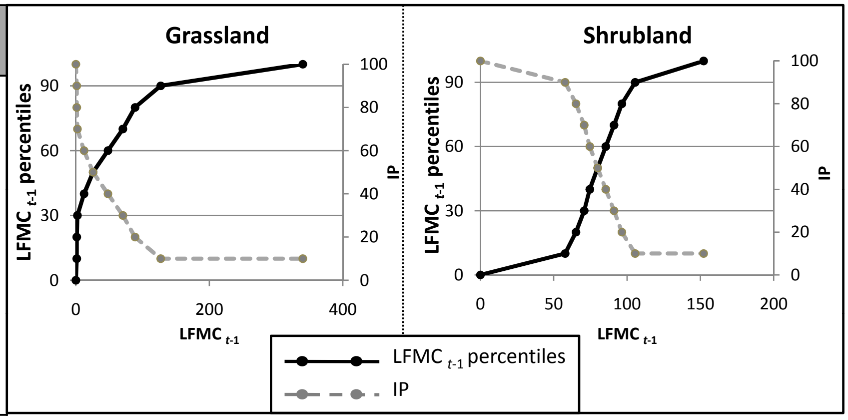

Figure 9. Percentile curves of LFMC$_{t-1}$ for fire pixels. The IP was computed by inverting the percentile values, so for low LFMC$_{t-1}$ values we have maximal IP. The ninetieth and tenth percentiles were the critical thresholds corresponding to the lowest and highest IP.

The IP was relatively high at terminal node 1 for all tree models (Figure 10). For instance, in the ES tree, the estimated IP at node 1 was 77 %. It has an interesting pattern defined as the pixels with LFMC$_{t-1}$ and slope below 111.04 % and –0.40, respectively. Taking into account that we have obtained three terminal nodes for ES, the resulting IP map would include just three IP categories: high IP, 77 %; medium IP, 34.1 %; and low IP, 15.4 %. In the case of the MS tree model, the IP map would also define three categories, whereas the EG tree model has only two categories: high and low. Finally, although the MG tree includes four terminal nodes, the cut-off at node 3 was for an LFMC$_{t-1}$ of 16.28 %. It is an anomalously low value in our data set. Therefore, the tree could be pruned at this split, ending up with two IP levels described by the first split.

The performance of the aforementioned models was assessed by means of the AUCs obtained from the ROCs for the test samples. Figure 11 contains the plots of the ROCs for all of the models. The ROCs given by the tree models provide good results; for example, the ES model captured nearly 80 % of fires, with 20 % false positives. We also observed (Figure 11), following the AUC, that the Eurosiberian region models perform better than the Mediterranean ones.

Logistic Regression Modelling

The logistic regression results indicated that, for the vegetation models, the AUC was 0.62 for grassland and 0.67 for shrubland (Tables 2 and 3). When we also considered climate, an improvement occurs, especially in the Eurosiberian region where the AUC was 0.87 and 0.81 for grassland and shrubland, respectively.

As previously obtained in the different methods, the LFMC$_{t-1}$ was the most relevant variable. It was included in all grassland models as well as in the Mediterranean shrubland model. The LFMC$_{t-2}$ was also found relevant in the Eurosiberian shrubland and in shrubland models as a whole. In addition, difference was included in the grassland model while slope was included in the shrubland model. The anomaly was included in some equations in order to account for atypically low moistures in relation to the historical records of the previous years. This is the case in ES, where the coefficient was sufficiently high to influence the results. However, it was found irrelevant in other models, as it was included with a very low coefficient.

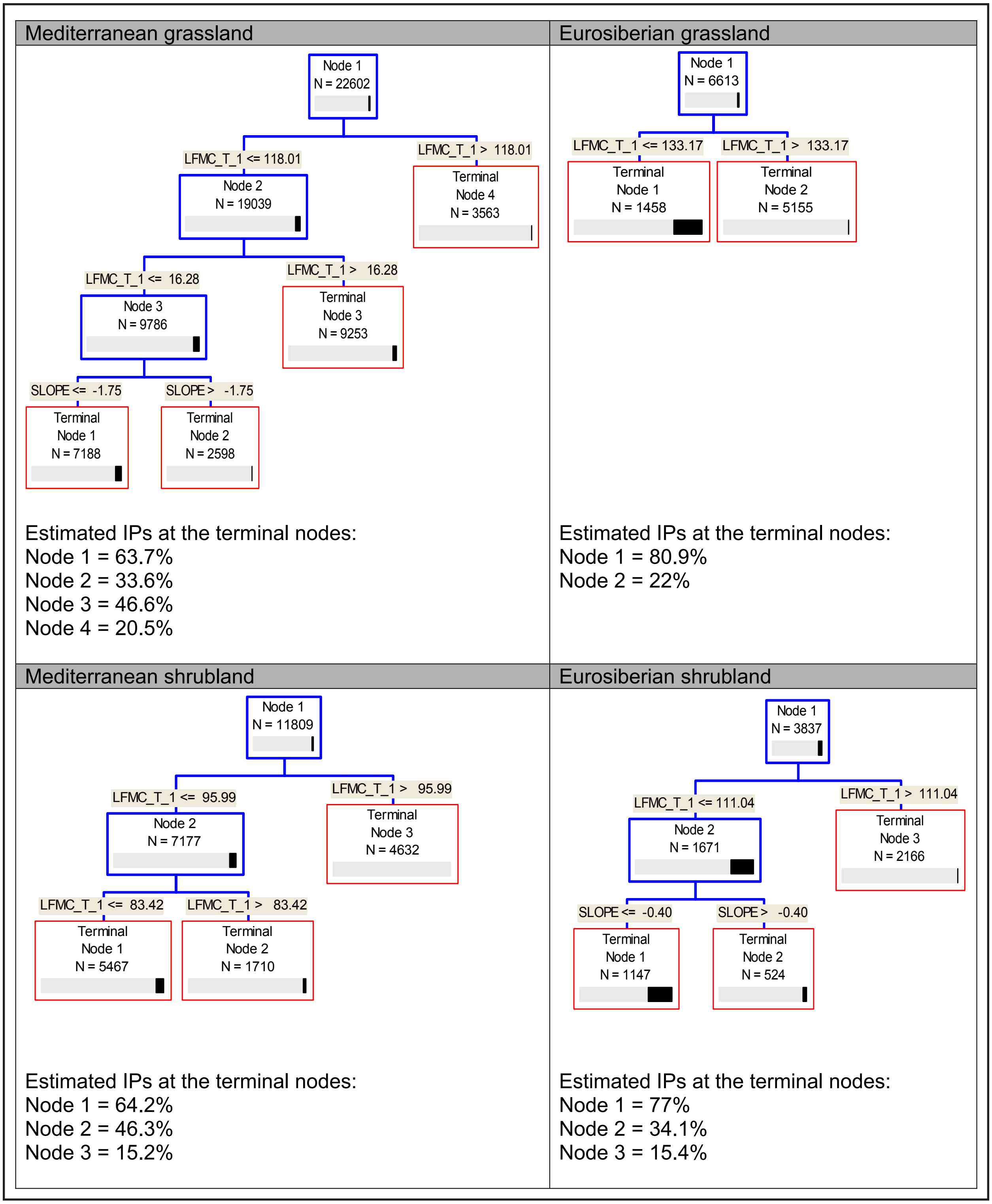

Figure 10. CART models and the estimated IPs at the terminal nodes given by the Bayes rule. The gray bars denote the amount of non-fire pixels; the black bars denote the amount of fire pixels. The first splitting variable was $LFMC_{t-1}$ and the IP was relatively high at terminal node 1 for all tree models.

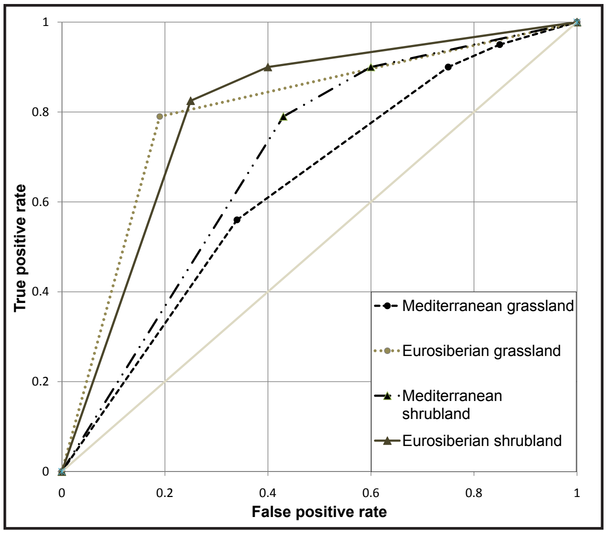

Figure 11. ROCs given by classification tree models with AUCs: MG = 0.65; EG = 0.79; MS = 0.7; ES = 0.8. The gray continuous line corresponds to the ROC of a random model (AUC= 0.5).

DISCUSSION

LFMC and Fire Pixels

The data showed an increasing IP trend as LFMC decreased. Lower LFMC values were associated with higher numbers of fire pixels, as it can be clearly observed in histograms and percentiles (Figures 7 and 9). This finding was also observed by de Groot *et al*. (2007), who concluded that as more local areas became dry enough to burn, there is a parallel increase in the number of hotspots. However, for both vegetation types, we found fires for high $LFMC_{t\text{-}1}$ values. It is possible to have high moisture one or two weeks before the fire, but just before the fire it can drop because of harsh meteorological changes or also due to moisture evaporation when vegetation is exposed to the heat of a nearby fire. That is one of the handicaps of not having a daily LFMC product.

Variables Selected in the Stratification Groups

In the most critical period for fires in Spain, grasslands usually have LFMC values much lower than shrublands (Figure 9), since they are severely affected by high temperatures and low precipitation in the summer months (García *et al*. 2008). Shrubs have more developed mechanisms to resist summer drought, such as leaf area reduction and non-photosynthetic material increment (Valladares 2004). Additionally, they have a greater capacity to extract

Table 2. Logistic regression results for grassland. $LFMC_{t\text{-}1}$ was the most relevant variable. The Eurosiberian grassland model showed the best performance with an Area Under the ROC curve of 0.87. The variables' coefficients considered in all of the models were found to be significant ($P < 0.001$).

	Variables in the equation	AUC
Grassland	$(-0.006*LFMC_{t\text{-}1}) + (-0.006*Difference) - 2.553$	0.62
Mediterranean grassland	$(-0.009*LFMC_{t\text{-}1}) + (0.001*Anomaly) - 2.696$	0.63
Eurosiberian grassland	$(-0.019*LFMC_{t\text{-}1}) + (-0.159*Slope) + (-0.004*Anomaly) - 0.004$	0.87

Table 3. Logistic regression results for shrubland. $LFMC_{t\text{-}2}$ and slope were the most relevant variables. The Eurosiberian shrubland model showed the best performance with an Area Under the ROC curve of 0.81. The variables' coefficients considered in all of the models were found to be significant ($P < 0.001$).

	Variables in the equation	AUC
Shrubland	$(-0.379*Slope) + (-0.017*LFMC_{t\text{-}2}) - 1.479$	0.67
Mediterranean shrubland	$(-0.023*LFMC_{t\text{-}1}) + (0.003*Anomaly) - 1.394$	0.68
Eurosiberian shrubland	$(-0.882*Slope) + (0.023*Anomaly) + (-0.039*LFMC_{t\text{-}2}) - 0.875$	0.81

water from the soil than grasses (García *et al*. 2008). Hence, shrubs are less dependent on weather conditions so their moisture decreases much more slowly, whereas grasses are more susceptible to rapid moisture changes. These factors help to explain why $LFMC_{t-1}$ and difference were included in the logistic regression grassland models (Table 2), while $LFMC_{t-2}$ and slope were included in the shrubland models (Table 3). Slope also appears as important in both vegetation types of the Eurosiberian region due to the higher moisture decline occurring in this area, with abundant spring rains and hot summers. In spring, variables exhibit fewer significant differences than in the other seasons (Figure 6). This is likely due to the higher soil water reserve in this season and, therefore, to the lower dependence of LFMC on meteorological variations.

Comparing Our Results with Previous Studies

Following previous studies, the ME was established at 105% for shrubs (Burgan 1979, Dimitrakopoulos and Papaioannou 2001). Our analyses showed that this LFMC corresponded to the ninetieth percentile, indicating that 90% of the shrubland fires in our study burned when LFMC conditions before the fire were at this value or lower (Figure 9). Additionally, this value appeared close to the first splitting values in the corresponding CART models (Figure 10). On the other hand, Dennison and Moritz (2009) developed a study on shrublands located in southern California, and found that large wildfires (>1000 ha) did not occur above a LFMC of 79%. In our case, the shrubland histogram has a peak at an $LFMC_{t-1}$ close to 80% (Figure 7). However, we also found a considerable number of fires above this value since we did not discriminate by fire sizes.

For grasslands (Figure 9), more than half of the fires occurred under the ME value of 40% (Albini 1976), but a significant number occurred above that threshold. This effect may be due to the impact of fires in agricultural areas (where fires are intentionally caused) or overestimations of the selected LFMC product, as there is an estimated mean LFMC error of 42.1% for this vegetation type (García *et al*. 2008). Therefore, the ninetieth percentile and the cut-off given by the first split in the grassland classification tree models reach higher values (close to 130%).

Many studies focused their interest on predicting fire risk based on antecedent weather or climate variables (Cohen and Deeming 1985, Renwick *et al*. 2007) highly related to fire occurrence. However, most of them based their predictions on meteorological variables. Hence, our findings are novel as they relate fire occurrence to the LFMC levels observed in one or two 8-day periods before the fire, as well as seasonal and annual trends of LFMC variation. In addition, our results are extremely useful since they offer the possibility of predicting fires one or two weeks before the beginning of the event, allowing fire managers to have more time to plan their strategies.

Comparing Methods

In regard to the methods used in this paper (Table 4), the first one, based on histograms and percentiles, offers a simple computation and interpretation, although it cannot deal with variable interactions since it conveys a univariate analysis. The CART and LR are more complex modelling tools and they have the advantage of handling multiple variables simultaneously. The CART provides simple profiles that are easy to interpret. However, the IP values at each node represent only the best description of the available data and may have limited predictive value. The number of nodes, and hence the number of IP levels, also differs among ecoregions. Unlike classification trees, LR modelling gives a continuous function, which makes the generation of IP from LFMC values easier and simpler. The ROC results obtained by LR are very similar to those obtained by CART (the AUCs were for MG ≈

Table 4. Characteristics of the modelling methods used.

Histograms and percentiles	CART trees	Logistic regression
Low complexity	High complexity	High complexity
Univariate analysis	Multivariate analysis	Multivariate analysis
Do not uncover variables interacting patterns automatically	It uncovers variables interacting patterns automatically	Does not uncover variables interacting patterns automatically
IP classes defined by the percentiles	IP classes defined by the nodes	IP defined by a continuous function

0.65, for MS ≈ 0.7, and for ES ≈ 0.8) although the former present slight improvements in the Eurosiberian grasslands (the AUCs obtained by LR and CART were 0.87 and 0.79, respectively). Since LR is additive in nature, it has the disadvantage of being unable to identify automatically multivariate LFMC factors highly correlated to fire occurrence; such complex LFMC patterns are easier to detect by CART.

As obtained from CART and LR analyses, the ROCs show a better performance for the Eurosiberian region models. This region has a great ecological diversity but is a smaller area in comparison to the Mediterranean region. The Eurosiberian region had 23.34 % of total fire detections but occupies only 15.57 % of the total Iberian Peninsula territory of Spain. Hence, the combination of smaller area and relatively more fires resulted in less variability and more accurate models. In contrast, in the vast Mediterranean region (it represents the 84.42 % of the total Iberian Peninsula territory of Spain) where the 76.65 % of the fire detections occurred, many factors are involved in fire ignition, which in turn gives less accurate models. Consequently, a more finely scaled ecoregionalization may improve these models.

Integrating LFMC Ignition Potential with Fire Risk Assessment

Fire risk indices are composed of human, climatic, ecological, and biophysical variables (Vidal *et al*. 1994). One of the key biophysical variables is the LFMC. Thus, thorough knowledge about its behaviour, both in the different regions and in the selected vegetation types, is of great importance. The methodologies employed in this work to obtain IP from a LFMC product were satisfactorily applied. However, the general philosophy involved in the construction of the specific fire risk index must be considered in order to choose the best index. In our case, the fire risk index within which this study has been developed (Chuvieco *et al*. 2010) includes the physical probability that a fire starts (IP) or propagates, and the potential damages that it may cause. Specifically, IP from LFMC is combined with the IP derived from dead fuel moisture content, as well as fire ignition data from lightning and human causes. To integrate IP from LFMC with the other factors, we have previously relied on a linear inverse function between actual LFMC and ME thresholds (105 % for shrubs and 40 % for herbaceous species (Chuvieco *et al*. 2004*a*). However, the results obtained in this study show the usefulness of the methodologies we have explored and how they can help to provide a more realistic IP model. These models could be specifically applied to the Mediterranean and Eurosiberian regions of the Iberian Peninsula territory.

Suggested Improvements

Our results should be contrasted with other study sites and probably longer time periods. Additionally, it should be pointed out that both our LFMC and fire occurrence data were estimated from external sources (AVHRR and MOD14, respectively), and therefore they include errors, which may affect the strength of the observed relationships. The water content estimates could be improved by the use of MODIS images as they have better spatial resolution (500 m). Yebra *et al*. (2008*b*) estimated LFMC from MODIS images comparing empirical methods and simulation approaches based on the inversion of radiative transfer models. The authors determined that the latter offered high accuracy ($r^2 = 0.894$ for grasslands and $r^2 = 0.842$ for shrublands) and greater robustness as empirical models. Hence, LFMC data derived from MODIS images based on simulation approaches would be the next step to improve the IP. Besides, we did not consider woodland in our analysis, so the study of the IP of this vegetation type would complement this research. In regard to the fire occurrence data, the official fire statistics in Spain started to include some UTM coordinates of ignition points in 2008, so their inclusion in IP models should be the next task. Then, with the mentioned improvements on the models, their applicability to other areas with similar characteristics is highly promising.

CONCLUSIONS

The present study showed several methodologies to estimate IP from LFMC. An important trait of this research was the design of the explanatory variables of fire occurrence, since an IP index with a wide range of high predictability was considered advantageous. Therefore, the selected variables were based on the LFMC one or two weeks before a fire, as well as on its seasonal and annual trends. As the variables' levels of importance varied for each spatial unit, the usefulness of developing specific models was demonstrated. The three methods investigated here were applied to convert the LFMC maps into an IP index, and were shown to be valuable tools for predicting fires. The first method was based on a study that included the most relevant variable for discriminating the fire and non-fire categories, the $LFMC_{t\text{-}1}$. In the second method, classification trees were utilized to classify fires according to a threshold of a variable related to the dependent variable, or to discover interacting patterns of variables (Dennison and Moritz 2009, Dimitrakopoulos *et al.* 2010), with the innovation of using the Bayes rule to assign an IP to each terminal node. Finally, several LR models were developed, obtaining an area under the ROC curve of around 0.65 for the Mediterranean region and above 0.8 for the Eurosiberian region. Since LR offers a specific IP for each pixel, it was considered an appropriate methodology highly convenient for our aim. Due to the specific strengths and weaknesses of CART and LR, future research efforts should incorporate a hybrid approach that combines both technologies.

The MODIS images (500 m of spatial resolution) are proposed to improve the LFMC data, and the inclusion of woodland is planned for future studies. Additionally, the applicability of the models to other areas will also be pursued. Finally, we should emphasize that LFMC is only one of the variables that is related to fire occurrence, and therefore the importance of other factors should also be considered for comprehensive characterization of fire risk conditions.

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LITERATURE CITED

Aguado, I., E. Chuvieco, R. Borén, and H. Nieto. 2007. Estimation of dead fuel moisture content from meteorological data in Mediterranean areas. Applications in fire danger assessment. International Journal of Wildland Fire 16: 390-397. doi: 10.1071/WF06136

Albini, F.A. 1976. Estimating wildfire behavior and effects. USDA Forest Service General Technical Report INT-30, Intermountain Forest and Range Experiment Station, Ogden, Utah, USA.

Andrews, P.L., D.O. Loftsgaarden, and L.S. Bradshaw. 2003. Evaluation of fire danger rating indexes using logistic regression and percentile analysis. International Journal of Wildland Fire 12: 213-226. doi: 10.1071/WF02059

Área de Defensa contra Incendios Forestales. 2006. Los incendios forestales en España. Dirección General de Medio Natural y Política Forestal. Ministerio de medio ambiente y medio rural y marino, Informe Técnico, Madrid, Spain. [In Spanish.]

Bartlett, J.E., J.W. Kotrlik, and C.C. Higgins. 2001. Organizational research: determining appropriate sample size in survey research. Information Technology, Learning and Performance Journal 19: 43-50.

Blackmarr, W.H., and W.B. Flanner. 1968. Seasonal and diurnal variation in moisture content of six species of pocosin shrubs. USDA Forest Service Research Paper SE-33, Southeastern Forest Experiment Station, Asheville, North Carolina, USA.

Breiman, L., J. Friedman, R. Olshen, and C. Stone. 1984. Classification and regression trees. Wadsworth International Group, Belmont, California, USA.

Burgan, R.E. 1979. Estimating live fuel moisture for the 1978 national fire danger rating system. USDA Forest Service General Technical Report INT-226, Intermountain Forest and Range Experiment Station, Ogden, Utah, USA.

Camia, A., B. Leblon, M. Cruz, J.D. Carlson, and I. Aguado. 2003. Methods used to estimate moisture content of dead wildland fuels. Pages 91-117 in: E. Chuvieco, editor. Wildland fire danger estimation and mapping. The role of remote sensing data. World Scientific Publishing, Singapore. doi: 10.1142/9789812791177_0004

Ceccato, P. 2001. Estimation of vegetation water content using remote sensing for the assessment of fire risk occurrence and burning efficiency. University of Greenwich, Ispra, Italy.

Chuvieco, E. 2008. Satellite observation of biomass burning: implications in global change research. Pages 109-142 in: E. Chuvieco, editor. Earth observation and global change. Springer, New York, New York, USA. .doi: 10.1007/978-1-4020-6358-9_6

Chuvieco, E., I. Aguado, and A. Dimitrakopoulos. 2004*a*. Conversion of fuel moisture content values to ignition potential for integrated fire danger assessment. Canadian Journal of Forest Research 34: 2284-2293. doi: 10.1139/x04-101

Chuvieco, E., I. Aguado, M. Yebra, H. Nieto, J. Salas, M.P. Martín, L. Vilar, J. Martínez, S. Martín, P. Ibarra, J. de la Riva, J. Baeza, F. Rodríguez, J.R. Molina, M.A. Herrera, and R. Zamora. 2010. Development of a framework for fire risk assessment using remote sensing and geographic information system technologies. Ecological Modelling 221: 46-58. doi: 10.1016/j.ecolmodel.2008.11.017

Chuvieco, E., D. Cocero, D. Riaño, M.P. Martín, J. Martínez-Vega, J. de la Riva, and F. Pérez. 2004*b*. Combining NDVI and surface temperature for the estimation of live fuel moisture content in forest fire danger rating. Remote Sensing of Environment 92: 322-331. doi: 10.1016/j.rse.2004.01.019

Chuvieco, E., I. González, F. Verdú, I. Aguado, and M. Yebra. 2009. Prediction of fire occurrence from live fuel moisture content measurements in a Mediterranean ecosystem. International Journal of Wildland Fire 18: 430-441. doi: 10.1071/WF08020

Cohen, J.D., and J.E. Deeming. 1985. The national fire-danger rating system: basic equations. USDA Forest Service General Technical Report PSW-82, Pacific Southwest Forest and Range Experiment Station, Berkeley, California, USA.

de Groot, W.J., X. Wardati, and W. Yonghe. 2005. Calibrating the fine fuel moisture code for grass ignition potential in Sumatra, Indonesia. International Journal of Wildland Fire 14: 161-168. doi: 10.1071/WF04054

de Groot, W.J., R.D. Field, M.A. Brady, O. Roswintiarti, and M. Mohamad. 2007. Development of the Indonesian and Malaysian fire danger rating systems. Mitigation and Adaptation Strategies for Global Change 12: 165-180. doi: 10.1007/s11027-006-9043-8

Dennison, P.E., and M.A. Moritz. 2009. Critical live fuel moisture in chaparral ecosystems: a threshold for fire activity and its relationship to antecedent precipitation. International Journal of Wildland Fire 18: 1021-1027. doi: 10.1071/WF08055

Dennison, P.E., M.A. Moritz, and R.S. Taylor. 2008. Evaluating predictive models of critical live fuel moisture in the Santa Monica Mountains, California. International Journal of Wildland Fire 17: 18-27. doi: 10.1071/WF07017

Dennison, P.E., and D.A. Roberts. 2003. The effects of vegetation phenology on endmember selection and species mapping in southern California chaparral. Remote Sensing of Environment 87: 295-309. doi: 10.1016/j.rse.2003.07.001

Dimitrakopoulos, A., and K.K. Papaioannou. 2001. Flammability assessment of Mediterranean forest fuels. Fire Technology 37: 143-152. doi: 10.1023/A:1011641601076

Dimitrakopoulos, A.P., I.D. Mitsopoulos, and K. Gatoulas. 2010. Assessing ignition probability and moisture of extinction in a Mediterranean grass fuel. International Journal of Wildland Fire 19: 29-34. doi: 10.1071/WF08124

Fielding, A.H., and J.F. Bell. 1997. A review of methods for the assessment of prediction errors in conservation presence/absence models. Environmental Conservation 24: 38-49. doi: 10.1017/S0376892997000088

Fink, A. 1995. The survey handbook. Sage Publications, Thousand Oaks, California, USA.

Finney, M.A. 1998. FARSITE: Fire Area Simulator—model development and evaluation. USDA Forest Service Research Paper RMRS-RP-4, Rocky Mountain Research Station, Fort Collins, Colorado, USA.

Fosberg, M.A., and M.J. Schroeder. 1971. Fine herbaceous fuels in fire danger rating. USDA Forest Service, Research Note RM-185, Rocky Mountain Forest and Range Experiment Station, Fort Collins, Colorado, USA.

Gandullo, J.M. 1994. Climatología y ciencia del suelo. Fundación Conde del Valle de Salazar, Madrid, Spain. [In Spanish.]

García, M., I. Aguado, and E. Chuvieco. 2008. Combining AVHRR and meteorological data for estimating live fuel moisture content in forest fire danger rating. Remote Sensing of Environment 112: 3618-3627. doi: 10.1016/j.rse.2008.05.002

Giglio, L., J. Descloitres, C.O. Justice, and J.B. Kauffmam. 2003. An enhanced contextual fire detection algorithm for MODIS. Remote Sensing of Environment 87: 273-282. doi: 10.1016/S0034-4257(03)00184-6

Goetz, S., G. Fiske, and A. Bunn. 2006. Using satellite time-series data sets to analyze fire disturbance and forest recovery across Canada. Remote Sensing of Environment 92: 411-423.

Green, L.R. 1981. Burning by prescription in chaparral. USDA Forest Service General Technical Report PSW-51, Pacific Southwest Forest and Range Experiment Station, Berkeley, California, USA.

Hawbaker, T.J., V.C. Radeloff, A.D. Syphard, Z. Zhu, and S.I. Stewart. 2008. Detection rates of the MODIS active fire product in the United States. Remote Sensing of Environment 112: 2656-2664. doi: 10.1016/j.rse.2007.12.008

Lawson, B.D., and B.C. Hawkes. 1989. Field evaluation of moisture content model for medium-sized logging slash. Proceedings of the Conference on Fire and Forest Meteorology. Ottawa, Canada 10: 247-257.

López-González, G. 1994. La guía de Incafo de los árboles y arbustos de la Peninsula Ibérica. Incafo, Madrid, Spain. [In Spanish.]

Martínez, J., C. Vega-García, and E. Chuvieco. 2009. Human-caused wildfire risk rating for prevention planning in Spain. Journal of Environmental Management 90: 1241-1252. doi: 10.1016/j.jenvman.2008.07.005

Morato, B. 2009. Validación de la localización de incendios mediante “global fire email alerts [BETA]” en áreas con clima Mediterráneo. Revista de Teledetección 31: 64-68. [In Spanish.]

Moreno, J.M., F.D. Pineda, and S. Rivas-Martinez. 1990. Climate and vegetation at the Eurosiberian-Mediterranean boundary in the Iberian Peninsula. Journal of Vegetation Science 1: 233-244. doi: 10.2307/3235660

Nelson, R.M. 2001. Water relations of forest fuels. Pages 79-149 in: E.A. Johnson and K. Miyanishi, editors. Forest fires: behavior and ecological effects. Academic Press, San Diego, California, USA.

Oliva, P., S. Jurdao, J. Martínez, and E. Chuvieco. 2008. Validación y comparación de los productos MODIS y AATSR para la detección de focos activos en la España peninsular y Baleares en el año 2003. Espacio, Tiempo y Forma 12: 141-150. [In Spanish.]

Pellizaro, G., C. Cesaraccio, P. Duce, A. Ventura, and P. Zara. 2007. Relationships between seasonal patterns of live fuel moisture and meteorological drought indices for Mediterranean shrubland species. International Journal of Wildland Fire 16: 232-241. doi: 10.1071/WF06081

Preisler, H.K., R.E. Burgan, J.C. Eidenshink, J.M. Klaver, and R.W. Klaver. 2009. Forecasting distributions of large federal-lands fires utilizing satellite and gridded weather information. International Journal of Wildland Fire 18: 508-516. doi: 10.1071/WF08032

Renwick, J., J. Salinger, X. Zheng, and G. Pearce. 2007. Prediction of fire weather and fire danger. New Zealand Fire Service Commission Research Report Number 83, Aukland, New Zealand.

Rivas Martínez, S. 1982. Series de vegetación de la región Eurosiberiana de la Península Ibérica. Lazaroa 4: 155-166. [In Spanish.]

Rivas Martínez, S. 1983. Pisos bioclimáticos de España. Lazaroa 5: 33-43. [In Spanish.]

Rivas Martínez, S. 1987. Memoria del mapa de series de vegetación de España 1:400 000. Instituto para la Conservación de la Naturaleza, Ministerio de Agricultura, Pesca y Alimentación, Madrid, Spain. [In Spanish.]

Rothermel, R.C. 1972. A mathematical model for predicting fire spread in wildland fuels. USDA Forest Service Research Paper INT-115, Intermountain Forest and Range Experiment Station, Ogden, Utah, USA.

Schoenberg, F.P., R. Peng, Z. Huang, and P. Rundel. 2003. Detection of non-linearities in the dependence of burn area on fuel age and climatic variables. International Journal of Wildland Fire 12: 1-6. doi: 10.1071/WF02053

Shafizadeh, F., P.S. Chin, and W.F. Degroot. 1977. Effective heat content of green forest fuels. Forest Science 23: 81-89.

Simard, A.J. 1968. The moisture content of forest fuels—a review of the basic concepts. Forest Fire Research Institute Information Report FF-X-14, Forestry Branch, Department of Forestry and Rural Development, Ottawa, Ontario, Canada.

SPSS. 2006. SPSS base 15.0 user's guide. SPSS, Chicago, Illinois, USA.

Tenhunen, J., W. Beyschlag, O.L. Lange, and P.C. Harley. 1987. Changes during summer drought in leaf CO_2 uptake rates of macchia shrubs growing in Portugal: limitations due to photosynthetic capacity, carboxylation efficiency, and stomatal conductance. Pages 339-355 in: J. Tenhunen, F.M. Catarino, O.L. Lange, and W.C. Oechel, editors. Plant response to stress-functional analysis in Mediterranean ecosystems. NATO ASI Series, Series G, Volume 15. Springer-Verlag, New York, New York, USA.

Trabaud, L. 1976. Inflamabilité e combustibilité des principales espèces des garrigues de la region Mediterranéenne. Oecologia Plantarum 11: 117-136. [In French.]

Valladares, F. 2004. Ecología del bosque Mediterráneo en un mundo cambiante. Ministerio de Medio Ambiente, EGRAF S.A., Madrid, Spain. [In Spanish.]

van der Werf, G.R., J.T. Randerson, L. Giglio, G.J. Collatz, P.S. Kasibhatla, and A.F. Arellano. 2006. Interannual variability in global biomass burning emissions from 1997 to 2004. Atmospheric Chemistry and Physics 6: 3423-3441. doi: 10.5194/acp-6-3423-2006

Vidal, A., F. Pinglo, H. Durand, C. Devaux-Ros, and A. Maillet. 1994. Evaluation of a temporal fire risk index in Mediterranean forest from NOAA thermal IR. Remote Sensing of Environment 49: 296-303. doi: 10.1016/0034-4257(94)90024-8

Viegas, D.X., T.P. Viegas, and A.D. Ferreira. 1992. Moisture content of fine forest fuels and fire occurrence in central Portugal. International Journal of Wildland Fire 2: 69-85. doi: 10.1071/WF9920069

Vilar, L., H. Nieto, and M.P. Martín. 2010. Integration of lightning- and human-caused wildfire occurrence models. Human and Ecological Risk Assessment: an International Journal 16: 340-364.

Weise, D.R., R.A. Hartford, and L. Mahaffey. 1998. Assessing live fuel moisture for fire management applications. Proceedings of the Tall Timbers Fire Ecology Conference 20: 49-55.

Wotton, B.M., and D.L. Martell. 2005. A lightning fire occurrence model for Ontario. Canadian Journal of Forest Research 35: 1389-1401. doi: 10.1139/x05-071

Yebra, M., E. Chuvieco, and I. Aguado. 2008*a*. Comparación entre modelos empíricos y de transferencia radiativa para estimar contenido de humedad en pastizales: poder de generalización. Revista de Teledetección 29: 73-90. [In Spanish.]

Yebra, M., E. Chuvieco, and D. Riaño. 2008*b*. Estimation of live fuel moisture content from MODIS images for fire risk assessment. Agricultural and Forest Meteorology 148: 523-536. doi: 10.1016/j.agrformet.2007.12.005