Fuel moisture estimation for fire ignition mapping

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Abstract

Fuel moisture content (FMC) is a critical variable for fire danger estimation since it affects fire ignition and fire propagation. Current methods for FMC estimation rely on meteorological data, which are good predictors of dead fuels, but they do not provide a reliable estimation of live fuels. Additionally, the integration of dead and live fuels is not commonly pursued.

This paper presents the results of a Spanish research project, that has tested the operational estimation of FMC from satellite data and meteorological danger codes for fire ignition probability mapping. Live FMC (LFMC) has been derived from NOAA-AVHRR and Terra-MODIS satellite data. Different models for grasslands and shrublands have been derived, using empirical and simulation approaches. FMC of dead fuels (DFMC) has been estimated from the 10h moisture code. In order to integrate dead and live FMC, both values have been converted to ignition probability using the moisture of extinction (ME). ME for dead fuels was taken from Behave fire simulation system, assigned values of 12% (model 1), 15% (model 2) and 25% (model 9), while for live fuels average values of 40% and 105% were used for grassland and shrublands respectively. Both indices have been mapped at 1 sq km spatial resolution, and will be integrated with other fire danger variables, within a comprehensive index of fire risk.

Introduction

Fuel moisture content (FMC) of both live (LFMC) and dead (DFMC), is one of the most important variables in fire ignition and fire behaviour modelling, and therefore is considered in most fire danger rating systems worldwide. Fuel water content is inversely related to the probability of ignition, due to the fact that part of the energy necessary to start a fire is used up in the process of evaporation right before the fire starts (Dimitrakopoulos and Papaioannou 2001). On the other hand, water content also affects fire propagation since the source of the flames is reduced with humid materials, therefore reducing flammability (Viegas 1998).

The estimation of FMC has been based on several methods, including field sampling, meteorological indices and remote sensing techniques. Field sampling is the most direct method, but it is also the most costly and his applicability to regional or global scales result unfeasible. Most operational fire danger rating systems base their estimation of FMC on meteorological data, routinely collected by national or regional weather services. Meteorological indices measure FMC indirectly, through the analysis of atmospheric characteristics from which vegetation water status is estimated, so their FMC estimations are reasonably well suited for dead fuels due to the fact that their water content is highly related to atmospheric conditions. However, live fuels have different physiological characteristics and adaptation to drought what make that a great diversity of moisture conditions can be found with the same

meteorological inputs (Viegas and others, 2001). Therefore meteorological indices are not appropriate for LFMC estimation. Remote sensing data (reflectance or surface temperature) are directly derived from vegetation conditions so they constitute a better alternative to estimate LFMC but not for DFMC. Dead materials, in one hand are under the vegetation canopy and consequently they are not directly remotely sensed and in the other hand, they are less sensitive to changes in radiance (Chuvieco, Aguado and others 2004).

For all above mentioned, an operational estimation of fire occurrence, giving a particular FMC should be derived from the jointly used of both meteorological danger codes and remote sensed techniques (empirical or those based on simulated data)

However, FMC is not the only variable to consider in a wildfire risk system. There are also others variables affecting the probability of occurrence, such as socio-economic factors. This creates severe difficulties for finding a common scale for combining all the fire danger variables in a synthetic index, especially when these variables are included as components of a geographical information system (GIS). GIS tools provide a comprehensive spatial view of fire danger conditions for local or regional planners since they facilitate the creation, transformation and combined analysis of geo-referenced variables. Consequently, GIS may portray the geographical location of those areas where danger factors are most severe and thus, fire protection programs may be spatially and temporally oriented to the areas labelled as having high fire danger rating levels. However, few fire danger systems are operationally using GIS technologies (Lee, Alexander and others 2002). This is mainly caused by the difficulties of generating the spatial distribution of some key variables, such as lightning activity or human factors (Chuvieco, Allgöwer and others 2003) and the difficult to integrate those different factors in the same "danger scale".

The use of GIS webmapping technologies and Remote sensing in a semi-operational application of fire danger assessment is the objective of the Firemap project, funded by the Spanish Ministry of Science and Technology, which tries to create an operational system to provide information on fire danger conditions to the fire managers in a daily basis. The danger index used for this project *(Fig. 1)* was based on a proposal made within the European Spread project (Chuvieco, Allgöwer and others 2003). Following its terminology, the term fire risk includes the probability that a fire occurs (danger) and the potential damage (vulnerability) of that fire on vegetation, soils, landscape, or properties. This latter aspect is not covered in this paper.

With regard to the danger component, the Spread project proposed to consider factors related to the probability of starting a fire (named ignition danger) and the potential likeliness that this fire propagates in space and time (termed propagation danger). The ignition danger is related to the causal agents of fire, as well as the conditions of the fuel, both dead and live, while the propagation danger refers to the predictable behaviour of the fire, caused by wind, slope and fuel load.

This paper addresses the role of FMC in fire ignition, and therefore the concept of fire danger is restricted here to the likelihood of fire occurrence, giving a particular fuel moisture content. This likelihood will be defined in terms of ignition potential associated to fuel moisture content status (identified as IPf). These values would be ready to be integrated with other variables associated with ignition sources (lightning, human), which could also be expressed in terms of ignition potential (IP_l and IP_h, for

ignition potential of lightning and human causes, respectively). In this way, the final value of ignition danger would be expressed in a common scale as a product of several ignition probabilities that would be included in a GIS-based fire danger rating system.

Figure 1: Framework of the Firemap project.
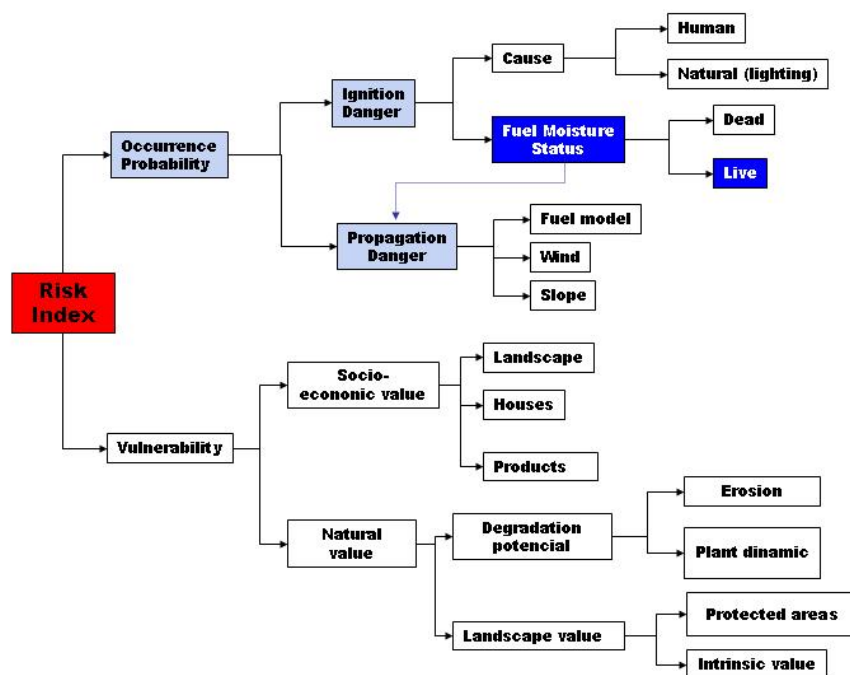
We start by proposing the methods used for LFMC and DFMC estimation and then the method to convert FMC to ignition potential. Finally, in spite of the fact that the Firemap fire danger assessment system was started in May of 2006 in four different regions of Spain (Aragón, Huelva, Madrid y Valencia), here we have selected a study case focused in the region of Madrid (Spain) for the 12th of August 2006.

Methodology:
Field sampling

A standard field campaign has been carried out in Cabañeros National Park (central Spain) from spring (April) to the end of the summer (September) in order to have LFMC and DFMC measurements and the critical biophysical parameters for generating the simulated dataset. LFMC samples of grasslands and several shrubland Mediterranean species (*Cistus ladanifer, Erica australis, Phillyrea angustifolia and Rosmarinus officinalis*) were collected from 1996 to 2005 each 8 or 16 days. The biophysical measures were performed in 2004 and 2005 for grassland and *Cistus ladanifer*, the later chosen as representative of the Mediterranean shubland species. DFMC samples consist on litter and cured grass collected from 1998 to 2003.

An extra field validation campaign was carried out in 2001 and 2002 in order to test whether LFMC models are applicable in other sites with similar environmental. This extra sites are in the autonomous region of Madrid (CAM), Castilla y León and Andalucía. In this case, LFMC was measured each 16 days. A detailed description of

the field work may be found in Chuvieco and others (2003) and (Yebra, Chuvieco and others).

Live fuel moisture content estimation

Empirical and simulation approaches for LFMC estimation as well as remotely sensed reflectance data at different spatial and spectral resolution were explored in order to determine which one offers the more accurate estimations.

Empirical methods were based on multivariate linear regression (MLR) analysis between field measured LFMC data (*Cistus ladanifer* and herbaceous species) and remoted sensed data derived from Terra-MODIS (Moderate Resolution Imaging Spectroradiometer) (Yebra, Chuvieco and others 2006) and NOAA-AVHRR (Advanced Very High Resolution Radiometer)

The MOD09A1 standard product of the Terra-MODIS program was chosen as source of MODIS atmospherically corrected reflectance. It is an 8-day composite for the first seven spectral bands of the MODIS sensor at a spatial resolution of 500 m (Vermote and Vermeulen 1999). The original products were downloaded from the Land Processes Distributed Active Archive Center (LP DAAC) of the United States Geological Survey (USGS) (http://edcimswww.cr.usgs.gov/pub/imswelcome/), reprojected from sinusoidal to UTM projection and resampled to a common resolution of 1 km using nearest neighbour method.

Daily 1 km NOAA-AVHRR images were acquired by the HRPT receiving station installed at the Department of Geography of the University of Alcala. Raw data were converted to reflectance using NOAA´s coefficients and degradation rates, and Surface Temperature (T_s) was derived using the methods proposed by Coll and Caselles (1997). Geometric correction was performed using orbital models, and multitemporal coregistration was assured using GCPs. Subsequently, daily images were composited using MVC-Brightness Temperature criterion.

The values of a given plot for comparing with the field data were extracted from each composite image (MODIS or AVHRR) using the median value of a 3x3 pixel kernel located at the center of the field plot. A 3x3 window was used in order to reduce the potential noise due to residual atmospheric effects and geo-referencing errors.

The inclusion of a temporal variable in the MLR analysis was also studied, as suggested by Chuvieco and others., 2004b, (Chuvieco, Cocero and others). This temporal variable, based on the day of the year (from 1 to 365), was considered to take into account seasonal trends in FMC. Two different functions, for each of the vegetation covers considered, were computed by empirically fitting a periodical function to the temporal average of FMC sampled values of grassland and *Cistus ladanifer* for dry years (1999 and 2005, eq. 1 and 2) and normal or wet years (the rest of the temporal series, eq. 3 and 4). Classification of dry/wet years was based on meteorological data available for Cabañeros site from 1998 to 2003 and 2005.

Dry years:

(1) $$FDp = (\sin(1.5 \times \pi \times (DJ + DJ^{1/3})/365))^6) \times 0.55$$

(2) $$FDm = (\sin(1.55 \times \pi \times DJ/365))^2 + 0.65) * 0.5$$

Normal years:

(3) $$FDp = (\sin(1.5 \times \pi \times (DJ + DJ^{1/2})/365))^6) \times 1.5$$

$$(4) \quad FDm = (\sin(1.6 \times \pi \times DJ/365))^2 + 1) \times 0.5$$

The simulation approach was tackled through the inversion of two well-known Radiative Transfer Models (RTM), Prospect (Jacquemoud 1990) at leaf level and Sailh (Verhoef 1984; Kuusk 1985) at canopy level. The inversion technique used was to built empirical relationships over RTM simulations and vegetation index derived from MOD09A1 simulated reflectance bands, as is explained in Yebra (2006). The range of variation of leaf biophysical parameters needed to run the models forward were taken from field measurements, while the viewing geometry and canopy structure were derived from MOD09A1 and MOD15A2 respectively and bibliography review. MOD15A2 is the MODIS leaf area index (LAI) product. It is generated daily at 1-km spatial resolution and composited over an 8-day period based on the maximum value of the photosynthetic radiation product for that period (Knyazikhin, Glassy and others 1999). MOD15 was acquired from the same URL site.

All the equations calibrated were validated using a MODIS or AVHRR validation dataset corresponding to the same study area where the models were calibrated (Cabañeros) but at a different dates. Those models which best performanced were validated in the extra study sites to test if they were equally good. In order to check the accuracy of the models the Root Mean Square Error (RMSE), which summarizes the difference between the observed and predicted FMC was computed. This RMSE was discomposed in systematic (RMSEs) which takes into account errors caused by uncontrolled factors and unsystematic (RMSEu) which considers errors caused by the model performance and the predictors included. A good model is considered to have an RMSEu much larger than the RMSEs.

Dead fuel moisture estimation

The efficiency of two well-known moisture codes to estimate DFMC in Mediterranean areas was tested in a previous work, adopting a two-step process (Aguado and others, in review). Firstly, an empirical model to estimate DFMC from meteorological data was developed by selecting the best adapted index to the Mediterranean areas. Secondly, the selected index was computed for a whole study region from weather forecasted data, using spatial interpolation techniques.

To test which meteorological danger index provided a better estimation of DFMC in Mediterranean conditions, a calibration phase was undertaken based on the field sampling carried out in Cabañeros National Park. Since our model was intended to estimate FMC of cured grasses and litter, it should be based on those meteorological indices associated to the finest dead fuels. Two moisture codes with this attribute were selected from the Canadian and the US fire danger indices: the Fine Fuel Moisture Code (FFMC) (Van Wagner 1987) and the 10-hour code, respectively (Bradshaw, Deeming and others 1983).

The selection of the most efficient index to estimate FMC of senescent grasses and litter was based on multitemporal correlation between the field data and the meteorological moisture codes. Yearly correlations were computed for each fuel type.

Linear regression analysis was conducted to obtain an empirical model for the estimation of FMC. Two separate models were created for grasses and litter, plus another one mixing the two fuel types. For all the regression models a random sample

of 70% of the study periods were selected to calibrate the model, and the remaining 30% were used for validation.

The performance of each index was measured by the Pearson r value and the root mean standard error (RMSE).

Considering the current difficulties to obtain and process data coming from numerous weather stations, it was decided to apply the spatial interpolation to forecasted variables, instead of to actual measured variables. Estimated fields of 14:00 GMT meteorological input variables for the Madrid region were obtained applying a two-step method. This method downscales and interpolates the surface temperature and relative humidity forecasts provided by European Centre for Medium Range Weather Forecasting (ECMWF) numerical weather prediction model (NWPM). Due to computational limitations, the horizontal grid resolution (0.5°x 0.5° in the ECMWF model) is not high enough to depict important topographical features. For this reason, in topographically complex regions -like Madrid- it became necessary to downscale NWPM output of surface variables. A statistical downscaling method, based upon empirical relationships between ECMWF forecasts and observations in 35 weather stations in the Madrid region were applied. Once the original 0.5°x 0.5° ECMWF forecasts were transformed into forecasts for 35 specific sites in the region, it was necessary to perform the spatial interpolation itself. The final output fields had a regular grid of 500x500 m resolution. The interpolation algorithm took into account horizontal distances between the grid point and the surrounding stations (quadratic inverse distance algorithm). The effect of altitude of each grid point over the value of the variable (temperature or humidity) was also considered by means of the variable/altitude gradient detected in the former prediction for the 35 sites since obviously they have different altitudes.

Conversion of FMC values to Fire Ignition Danger

Once the estimation of FMC was accomplished, the final step was to convert both LFMC and DFMC to a common scale of fire danger in order to be able to integrate them with other factors of fire risk. This common scale was defined in terms of probability of fire occurrence, either related to human factors or physical factors. In this sense, all those danger variables will be transformed into a common scale of danger, ranging from 0 (null probability) to 1 (maximum probability). The probability of fire occurrence associated to FMC was based on the concept of moisture of extinction (ME) that was successful tested in a previous project (Chuvieco, Aguado and others 2004). ME is defined as the threshold moisture content above which a fire cannot be sustained (Rothermel 1972). In spite of some criticism, this concept is widely used in forest fire literature (Burgan, Klaver and others 1998). ME of dead fuels varies between 12-40% depending of fuel types. For the types of dead fuels used in this study, ME values were taken from the BEHAVE fire behaviour prediction system (Burgan and Rothermel 1984). Grasslands with FMC values lower than 30% were considered as dead fuels and assigned ME values of 12% (model 1) and 15% (model 2). Likewise, the ME value for litter was 25% (model 9). For live fuels, ME threshold values were taken from specialized literature. For shrubs, an average value of 105% was selected, for annual grasslands the ME threshold was fixed at 40% (Chuvieco, Aguado and others 2004).

We assumed that ME values act as relative thresholds to ignition for each fuel, above which the ignition potential dramatically decreases. Although, the ignition probability

(IP) for FMC values higher than ME should be zero, a conservative approach was followed, assuming that a marginal IP existed even at high values of FMC. For this reason, Chuvieco (2004) proposed to assign a maximum IP of 0.2 to the FMC that equals the ME value of each fuel. FMC values lower than ME would have IP values in the range of 0.2 to 1, the IP being linearly inversely proportional to FMC values. For FMC values greater than the ME, IP values would range from 0.2 to 0. Null ignition potential (IP = 0) was assigned to the maximum FMC value recorded in the historical series of FMC field measurements (1996-2005). Schematically this method is based on the following algorithm:

If FMC > ME then

$$IP = (1 - ((FMC - ME) \div (FMC_{max} - ME))) \times 0.2 \text{ Else}$$

$$IP = (0.2 + (ME - FMC) \div (ME - FMC_{min})) \times 0.8$$

where FMC_{max} and FMC_{min} are the maximum and minimum FMC values of each fuel type derived from field FMC samplings. Although these values are site specific, they can reasonably be applied to relatively large regions that have similar environmental conditions. After applying this algorithm, Ignition Probability values associated to FMC in live fuels (IP_{live}) and dead (IP_{dead}) were obtained .

In order to integrate IP_{live} and IP_{dead} in the IP_f concept we have account the fuel load associated to each BEHAVE fuel model. The estimated IP_f was obtained using the next equation:

$$IP_f = (IP_{live} \times \%livefuelload + IP_{dead} \times (100 - \%livefuelload)$$

Where *%livefuelload* stands for the proportion of live fuel load within each grid related to land use cover extracted from the Corine Landcover 2000.

Results

Live fuel moisture content estimation

The calibrated models for LFMC estimation are showed in *table 1*. With regard to grassland models, there are little differences between their determination coefficients (R^2) and standard errors (SE). All the independent variables had significance values lower than 0.01. However, MODIS derived models have slightly higher R^2 and lower SE. Similar adjustments are also found for shrublands models and all the independent variables are significant at 99% but GVMI of model 2 which is significative at 90 %. The model 1 performs somewhat poorer as it has the lowest R^2 and highest SE.

The validation results *(table 2)* show that every grassland models have R^2 about 0.9 and FMC estimated-observed relations close to 1:1 slope. RMSE values are also quite similar having the model with highest value (model 2) an RMSE 6 % higher than the model with the lowest one (model 3). The model 3 derived from MODIS and RTM, has a slightly lower tendency to overestimate. However, it is less operative, as it includes information from two different MODIS products (MOD09 and MOD15), so as their estimations do not extremely improve the accuracy, in balance it is no worth use it. In conclusion, model 1 is considered the most appropriated.

Table 1. *Gras (G) and Shrub (S) calibrated models. R^2 is the determination coefficient, SE, Standard error, NDVI "Normalized Difference Vegetation Index"(Rouse, Haas and others 1974), NDII "Normalized difference infrared index" (Hunt and Rock 1989), VARI "Visible Atmospheric Resistant Index" (Gitelson, Kaufmam and others 2002), GVMI "Global Vegetation Moisture Index" (Ceccato, Gobron and others 2002). FDx is the function of the Day of the year (as stated in equations 1 to 4), T_s is the surface temperature, DM the "Dry matter content" and LAI "Leaf area index".*

	SENSOR	METHOD	MODEL	R^2	SE (pct)
G	MODIS	Empirical	1. $FMC_G = -161.1 + 650.2 \times NDVI$	0.91	30.1
		Empirical	2. $FMC_G = -129.12 + 503.51 \times NDVI + 52.55 \times FD_G$	0.93	26.3
		RTM	3. $FMC_G = -6.7 + 131.4 \times LAI + 296.7 \times NDII$	0.89	29.5
	AVHRR	Empirical	4. $FMC_G = 27,95 + 115,51 \times FDp + 331.86 \times NDVI - 1,194 \times T_s$	0.85	36.9
S	MODIS	Empirical	1. $FMC_S = 229.1 + 887.2 \times VARI - 300.7 \times GVMI$	0.73	17.5
		Empirical	2. $FMC_S = 104.38 + 427.57 \times VARI - 163.67 \times GVMI \times 88.44 \times FD_S$	0.78	15.2
		RTM	3. $FMC_S = 200.3 - 5322.8 \times PE + 92.3 \times GVMI$	0.82	12.9
	AVHRR	Empirical	4. $FMC_S = 8,73 + 125,87 \times FD_S + 40,79 \times NDVI - 0,2294 \times T_s$	0.81	13.3

Table 2. *Validation of the models Cabañeros National Park site. RMSE stand for Root Mean Square. RMSEs and RMSEu, systematic and unsystematic portions respectively*

VEGETATION	MODEL	R^2	Slope	Const.	RMSE (pct)	RMSEs (pct)	RMSEu (pct)	BEST
GRASS	1	0.91	0.93	12.69	27.38	10.34	25.40	2
	2	0.87	0.93	14.70	33.41	11.90	31.22	4
	3	0.93	0.92	0.17	24.57	8.69	23	1
	4	0.91	0.89	10.46	27.43	13.50	23.88	3
SHRUB	1	0.73	0.922	9.75	16.03	3.43	15.66	1
	2	0.68	0.768	28.67	17.79	9.96	14.74	2
	3	0.56	0.513	23.03	23.04	19.30	12.57	4
	4	0.76	0.819	22.40	14.30	7.44	12.21	3

With regard to shrubland models, their determinant coefficients are lower than for grassland. Model 3 has the lowest R^2 and highest RMSE, being its systematic portion higher than the unsystematic one. This all indicates that this model should be discarded. Model 4, derived from AVHRR, has the second best adjustment but it shows a higher tendency to overestimations as it is confirmed by the constant of the validation fitting. It is concluded that model 1 is again the most appropriate as its relation between observed and estimated is the closest to 1:1 slope.

The assessment of these equations on the other study sites shows no such a good results as it was expected *(table 3)*. Grassland model 1 has a RMSE of 42.6 % and a high tendency to overestimate. On the other hand, shrubland model 1 has a R^2 equal to 0.63. Due to the fact that models 2 were not much worse than the models 1, their performance was tested in this validation sample. The result is that grassland and shubland models 2 perform better than models 1 in these sites because their determinant coefficients are higher and the tendency to overestimate is lower (grassland model). Because of this, models derived from MODIS data which include the Julian day function (model 2) are chosen for both, grassland and shrubland.

Table 3. *Validation of the Grassland (G) and Shubland (S) models in other sites. RMSE stand for Root Mean Square. RMSEs and RMSEu, systematic and unsystematic portions, respectively.*

|	MODEL	R^2	Slope	Const.	RMSE (pct)	RMSEs (pct)	RMSEu (pct)	BEST
G	1	0.88	0.78	36.39	42.6	27.56	32.48	2
	2	0.90	0.85	18.17	36.08	16.5	32.09	1
S	1	0.63	0.90	-8.26	27.98	18.10	21.34	2
	2	0.85	0.90	-0.40	10.47	11.71	15.71	1

Dead fuel moisture estimation

A comparative analysis of the relationship between the adjustment of observed and estimated FMC from the FFMC and that from the 10-h code did not show significant differences, according to the data shown. Consequently, the 10-h code was selected for the remaining phases of this study, as it requires fewer meteorological variables for its calculation (temperature and relative humidity). In order to make operational the FMC estimation we have assessed the possibility of using a joint equation for both fuel models (cured grass and litter). The resulting coefficients from this analysis are:

$$FMC = 10h \times 1.0317 + 2.1608$$

The results of the data used to validate the model (30% of the sample) did not differ from the rest of the sample.

Fig. 2 shows the fit between observed and predicted FMC values for the validation data using the 10h code. The adjustment is stronger in the cured grass because of no outstanding deviations in the estimations. In terms of the litter fuels, there was a deviation between observed and estimated values of the FMC in some rainy periods. The remaining time periods show a generalized tendency toward overestimation of the water content value of this type of fuel.

**Figure 2**: *Observed and predicted dead FMC values for the validation data. ( ) Cured grass, (•) Litter*
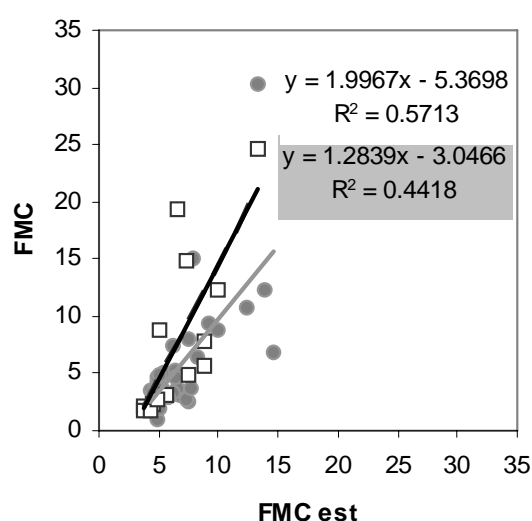
Estimated values of 14:00 GMT temperature and relative humidity (at 2m height from the surface), for the Madrid region, were obtained applying the two-step method previously described. This method is currently operative to supply high-quality, high-resolution forecasts of forest-fire related meteorological variables in many regions in Spain and were provided by *Meteológica S.A*.

Conversion of FMC to Igniton Probability

To obtain the moisture of extinction and fuel load available of each grid of the Madrid region, a fuel type map was provided by the Regional Environmental Office. For the types of dead fuels used in this study moisture of extinction were derived from those proposed in the BEHAVE fuel models (Burgan and Rothermel 1984). Fig. 3 shows an example of IP_{live} , IP_{dead} and the IP_f computed the 12th of August 2006.

Figure 3: *Example of IP_{live} (a) , IP_{dead} (b) and the IP_f (c) computed for the 12th of August in Madrid.*
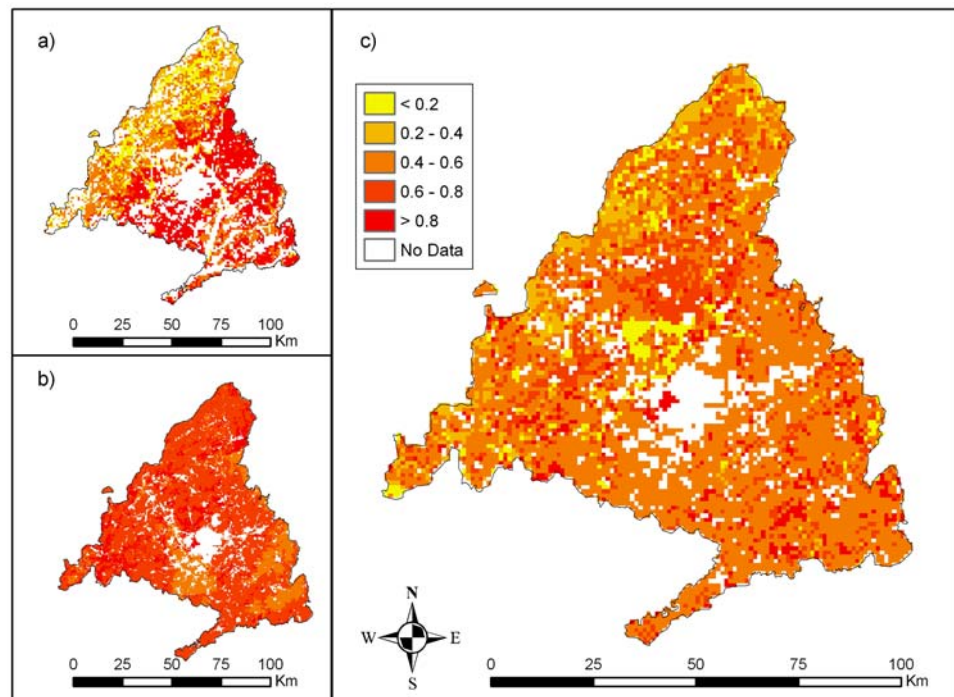
With regard to IP_{live} , lower values (mainly between 0-0.4) are found from the north to the south-west border of the region, coinciding with the mountain areas; "Sierra Norte", "Cuenca alta del Manzanares", "Cuenca del Guadarrama" and "Sierra Oeste". In these areas the values of LFMC are high and close to the maximum LFMC values recorded in the historical series of LFMC field measurements (340% and 210% for grass and shrubland, respectively) and to the ME value (105%). The reason of this is that the vegetation dominated at higher altitudes by shrubland is not affected by water shortage (the rainfall is above 800 mm). However, some elevated IP_{live} values (0.6 - 0.8) are also found coinciding with mid-elevation grassland which, although remain green longer than the grassland in the southern part, they also reach moisture levels lower than 40% (grassland ME) at the middle of the summer periods. This is mainly due to the high temperatures and lower precipitations that are reached

in this season. Some empty pixels are found in woodland areas since this kind of cover was not dealt in this paper.

Values range 0.6-1 are found in the central and south-east part of the autonomous community where the mountains disappear giving rise to the Tajo Valley plain. This valley is on sands, loams and clays and it is dominated by moors and large areas of cultivated land. The central area is where a higher quantity of no data is found since it coincides with the metropolitan area.

Finally, middle IP_{live} values dotted with high values and no data pixels are found in the south-east fertile plain part of the region of Madrid. This is mainly dominated by crops and gallery communities and therefore the high quantity of no data is also explained.

Regarding to dead fuels less variability in their IP values are found. There are no values lower than 0.4 in any part of the study region. This is due to the high temperatures and low relative humidity that combined produce the lowest DFMC values. A slightly tendency over higher values from north-west to south-east is found due to the altitudinal gradient.

Having a look to the final map resulting from the combination of both IP_{live} and IP_{dead}, a higher heterogeneity in the IP_f values is found, although middle values (0.4-0.6) dominate the region.

Conclusions

This paper has tried to show a simple procedure to integrate FMC information into fire danger assessment systems, focusing on its integration into ignition danger rating. Since fire ignition is a result of several variables associated to causal agents and fuel water status, a common scale of danger is required to integrate those variables into a synthetic danger index. We propose to transform the original scale of each danger variable into an ignition potential (IP), defined as the likelihood of a starting fire, in the range of 0 to 1. This likelihood can be related to the action of causal agents, such as lightning or human activities, as well as to the water status of fuels. Methods to convert all these variables to IP are required. This paper has presented a method to obtain the IP associated to fuel moisture content.

Within this framework, we proposed to compute the ignition potential associated to fuel water state (IP_f), based on the concept of moisture of extinction (ME), which expresses a physical threshold for flammability. The function to convert FMC into IP is a linear one, since for Mediterranean species it has been found a continuous increase in flammability as FMC reduces.

Since FMC can be mapped either by gridded meteorological data or satellite images, IP_f can also be mapped, and therefore the assessment of ignition danger can be spatially performed. Moreover, this information can be easily integrated with other sources of danger (lightning or socio-economic causes), in the framework of Geographic Information Systems developed for this purpose. The spatio-temporal comprehensive view of such products should be very helpful to fire managers, who can make decisions within the spatio-temporal context. Additionally, this information may be overlaid with maps showing the available dispatch resources or the potential effects of fire on human and natural resource, thus improving the selection of the most appropriate fire prevention activities.

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