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Published in:
Remote Sensing of Environment

DOI:
10.1016/j.rse.2008.05.002

Publication date:
2008

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

Citation for published version (APA):
Combining AVHRR and meteorological data for estimating live fuel moisture content

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ARTICLE INFO

Article history:
Received 31 January 2008
Received in revised form 6 May 2008
Accepted 10 May 2008

Keywords:
Forest fire danger
Life fuel moisture content
AVHRR
Drought index
CWBI

Abstract

Spatial assessment of fire risk is very important for reducing the impacts of wildland fires. Several variables related to fire ignition, propagation and its effects are included in fire risk analysis. Life Fuel Moisture Content (LFMC) is one such variable, which is highly related to fire ignition, and propagation. A wide variety of methods have been applied to estimate LFMC, including field sampling and meteorological indices. Given the limitations of these methods, satellite images are a sound alternative for estimating LFMC because of their capability to spatially and temporally monitor the vegetation status. This paper aims to improve previous empirical models to estimate LFMC from satellite images, by considering meteorological information. The original models proposed by Chuvieco et al. [Chuvieco, E., Cocero, D., Riaño, D., Martin, M.P., Martinez-Vega, J., et al., (2004). 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] for grasslands and shrubs were used as starting point for this research. High over-estimation of LFMC values from those models was found when applied to dry years. Consequently, the new models proposed in this paper use a simple drought index to discriminate between dry and wet years at the beginning of the spring season. A different harmonic function was fitted to each group of hydrological years, to take into account the inter-annual variations in LFMC seasonal trends. Subsequently, two empirical models, one for grasslands and one for shrubs (Citrus ladanifer), were derived based on multivariate linear regression analysis of the data collected at Cabañeros National Park (Central Spain). Determination coefficients greater than 0.8 for grasslands and 0.7 for shrubs were found. The models showed good performance too when applied to other plots of grasslands ($R^2=0.76$) and shrubland ($R^2=0.71$) with similar environmental characteristics to the calibration site.

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1. Introduction

Plant moisture content is a critical variable to understand different eco-physiological processes (Slavik, 1974). Among other applications, moisture content has been used to estimate fire danger conditions (Ceccato et al., 2003). Within this context, the term live fuel moisture content (LFMC) is commonly used. LFMC is highly related to fire ignition and propagation. Plants with low moisture content are easier to ignite, since water increases ignition delay. Additionally, water acts as a heat sink; slowing down the spread and intensity of fire (Viegas et al., 1992). Fuel moisture content (FMC) is commonly defined as follows:

$$FMC = \frac{W_{w}-W_{d}}{W_{d}} \times 100$$

Where $W_w$ is the wet weight of a given sample and $W_d$ is the weight of the same sample, usually after oven drying at 60 °C–100 °C for 24–48 h (Viegas et al., 1992). This index is used to estimate the moisture content of both live and dead fuels.

In remote sensing applications, the water content of plants is commonly expressed using the Equivalent Water Thickness (EWT, defined as the water content per leaf area). This measure has been related to absorption features in different spectral wavelengths, and is therefore easily retrieved from remote sensing measurements (Ceccato et al., 2001). FMC and EWT can be related using the dry matter content, which is a common variable in radiative transfer models (Danson & Bowyer, 2004; Yebra et al., 2008).

Several methods have been used to estimate LFMC. Field sampling is the most direct and simple method, but it is costly and difficult to apply at regional or global scales (Ceccato et al., 2003). Consequently, most operational fire danger rating systems use meteorological indices to estimate fuel moisture content. Meteorological indices are mainly applied to estimate the FMC of dead fuels (Aguado et al., 2007; Viney, 1991), which are more directly related to atmospheric conditions than live fuels and are easier to ignite. Given the capability of live plants to control stomatal conductance and to extract water from the soil reservoir under drought conditions (Vitale et al., 2007), the application of meteorological indices to live fuels is less direct than to dead fuels. In addition to this problem, meteorological indices can only be computed for the sites where weather stations are located and therefore further interpolation is required to obtain a comprehensive spatial estimation of moisture...
conditions. Despite the difficulties of applying meteorological indices to live plants, several drought indices have been linked to LFMC in Mediterranean environments and shown good agreements (Castro et al., 2003; Dennison et al., 2003).

Satellite images offer appropriate methods for spatially and temporally monitoring vegetation conditions and subsequently offer a sound alternative to field sampling and meteorological indices, as a means of estimating LFMC. Different methods have been proposed using optical, thermal and microwave data to estimate LFMC. Vegetation indices have been widely used to estimate LFMC generally based on empirical fittings from coarse resolution data, such as NOAA/AVHRR or MODIS imagery (Chlaidil and Nunez, 1995; Chuvieco et al., 2004, 2002; Paltridge & Barber, 1988). Results from grasslands have generally been satisfactory, but estimation of shrub species has been more problematic (Alonso et al., 1996; Hardy & Burgan, 1999). The variation of water content in grasslands is associated to variations in chlorophyll activity and leaf area index (Running et al., 1995), while in shrubs both variations are less evident. Some researchers have proposed spectral indices based on the water absorption characteristics, using the near infrared and the short wave infrared wavelengths, which have been proved to be the most sensitive to water content variations (Ceccato et al., 2002; Danson & Bowyer, 2004; Gao, 1996). Other researchers have used thermal imagery to estimate vegetation water stress based on the effect that the amount of available water has on the plant energy balance process (Sandholt et al., 2002; Vidal et al., 1994). Combining spectral indices with thermal data to estimate LFMC has shown better correlations with water content than using either of the two variables alone (Chuvieco et al., 2004; Sandholt et al., 2002). Within the microwave spectral region, Leblon et al. (2002) found significant relationships between rates of change in LFMC and radar backscatter (σ°) in boreal forest.

Simulation approaches, generally based on inversion of radiative transfer models (RTM), have also been developed to estimate LFMC from satellite imagery (Ceccato et al., 2001; Ceccato et al., 2002; Riaño et al., 2005; Zarco-Tejada et al., 2003). Several authors have discussed the advantages of radiative transfer models over empirical models to estimate LFMC (Yebr et al., 2008). Unlike empirical models, simulation approaches are independent of sensor and site characteristics, but they require an appropriate parameterization to build simulation scenarios that are realistic enough, since RTM are based on assumptions that may not represent those found in nature (Liang, 2004).

2. Background and objectives

Among the various empirical models that have been proposed to estimate LFMC from satellite data in recent literature, we selected the one suggested by Chuvieco et al. (2004) to provide operational estimations of fire danger conditions. The selection was based on its adequacy to Mediterranean conditions and high accuracy. Chuvieco et al.’s model was based on Advanced Very High Resolution Radiometer (AVHRR) images on board the NOAA satellite. The study period was 1996 to 1999 for calibration and 2000 and 2001 for validation. Two equations for grasslands and shrub species were computed using multivariate linear regression (MLR). The input variables were the Normalized Difference Vegetation Index (NDVI) and Surface Temperature (ST) data derived from 8-day maximum NDVI value composites of daily AVHRR images and a function of the day of the year. The final equations were:

\[ FMC_g = -57.103 + 284.808 \times NDVI - 0.089 \times ST + 136.75 \times FD_g \]  (2)

\[ FMC_c = 70.195 + 53.520 \times NDVI - 1.435 \times ST + 122.087 \times FD_c \]  (3)

Where:

FMCg and FMCc are the estimated fuel moisture content for grasslands and shrubs (Cistus laudanifer) respectively, and FDg and FDc are functions of the day of the year. These models to estimate LFMC will be referred to as the Reference Models (RM) throughout this paper. The RM showed a consistent estimation of LFMC, with R² values higher than 0.8 for the different sites and species considered. However, the application of the model to a longer time series revealed poor performance for severe dry years (as it occurred in 2005: Fig. 1), which caused a high under-estimation of fire danger conditions. Conversely, the LMFC was under-estimated in very wet years, such as 1996 and 2000. This error is less critical in the context of fire danger assessment, which mainly aims to identify critical conditions leading to fire ignition or propagation. It was also observed that the RM sometimes produced negative estimations of LFMC values for the summer period of both dry and wet years (Fig. 1).

The problems with extreme years hampered the operational application of the RM and made it advisable to review the previous approach for estimating LFMC. The main goal of this paper is to update the RM as to be more robust for different rainfall conditions. The new model considered uses different equations for dry/wet years, to avoid the averaging trend observed in the RM. As a result, this paper proposes a dual model, based on the characteristics of the hydrological years up to the beginning of the spring season. The revised methodology includes data from three additional years (2003–2005) to those used initially in building and validating the RM, thus extending the variability of the time series.

The new models were calibrated and validated using field data collected in the Cabañeros National Park (central Spain, Fig. 2).
Additional sites were used to spatially validate the method. Moreover, in order to assess the benefits of the dual model approach, its results were compared to those obtained by applying the RM.

3. Methods

3.1. Field sampling

Field sampling of LFMC was carried out in the Cabañeros National Park from 1996 to 2005. The study area includes homogenous areas of grasslands and shrubs on very gentle slopes. Three plots of annual grasslands were sampled 5 km apart. Two plots of shrubs that contain several of the most typical Mediterranean species (C. ladanifer, Erica australis, Philyrea angustifolia and Rosmarinus officinalis) were also sampled. Three samples per species were collected for each plot and period and the average value was used for further processing.

Samples were collected from early spring (April) to the end of the summer (September) every 8–16 days. This covered the most critical period for forest fires in Spain. Additionally, LFMC data collected in different regions during 2000 and 2001 were used for spatial validation purposes. The validation plots were as far as 500 km from the Cabañeros calibration site and represented different elevations but similar species. Grassland validation measurements were performed at Ávila, Segovia and Madrid, whereas shrubland validation data were collected at Andaucia, Aragón and Madrid. Only those plots which have a similar composition to the Cabañeros plots, i.e. with a fractional cover of C. ladanifer or R. officinalis higher than 60% were considered in the analysis.

A complete description of the field work can be found in Chuvieco et al. (2004).

3.2. Image processing

Daily images were acquired by the AVHRR High Resolution Picture Transmission receiving station installed at the Department of Geography of the University of Alcalá. Radiometric calibration was performed based on coefficients provided by NOAA, including temporal degradation rates. The images were geometrically corrected using orbital models. In order to assure the geometric matching of the images, the geometric correction was improved using automatic image matching and Ground Control Points from a reference image, resulting in a RMSE=1 pixel in all cases.

After correcting the images, the NDVI and the ST were computed. ST was based on the method proposed by Coll and Caselles (1997). During 2004–2005 the sensor on board NOAA-16 satellite failed, which precluded its use. Thus, AVHRR images from NOAA-17 were used instead. This satellite’s crossing time is about 2–3 h earlier than NOAA-16. Therefore, the ST derived from NOAA-17 acquisitions was expected to be cooler than those estimated from NOAA-16. A similar effect was observed by Coops et al. (2007), who proved the significant difference in ST values derived from the morning Terra-MODIS and the afternoon Aqua-MODIS overpasses. Coops et al. (2007) found a good linear correlation between those two temperatures and subsequently derived a linear model to estimate the afternoon ST from data collected during the morning overpass. Following a similar methodology, we adjusted the ST derived from the NOAA-17 images to the afternoon conditions, thus making the time series more compatible. The correction was based on the following equation:

\[ \text{ST}_{\text{NOAA-17}} = -1.239 + 1.131 \times \text{ST}_{\text{NOAA-16}} \]  

Where, \( \text{ST}_{\text{NOAA-16}} \) is the estimated temperature at NOAA-16 crossing time from NOAA-17 measurements. The determination coefficient obtained was 0.93 (\( p<0.001 \)).

Daily images were then synthesized into 8-day composites using the maximum value of the brightness temperature (AVHRR-Ch 4) as composing criterion. Though initially proposed for burned land mapping, this criterion was found by Chuvieco et al. (2005) as more suitable than the maximum NDVI values for the reduction of image artefacts (cloud and cloud shadows), while assuring close to nadir observations, and a good spatial coherency of the composite images. Finally, the median value of a 3×3 window at each of the field sampling plots was extracted from each composite image for comparison with field LFMC measurements.

3.3. Classification of dry/wet years

Since the RM showed a clear over-estimation when applied to dry years, the new approach to the estimation of LFMC values was based on two models, one for grasslands and one for shrublands, which take into account the influence of dry and wet years on LFMC seasonal trends. This approach emphasises the seasonal and inter-annual variation of precipitation and evapotranspiration in Mediterranean ecosystems. Dennison and Roberts (2003), proposed a simple index for measuring regional drought stress, the Cumulative Water Balance Index (CWBI), which was successfully related to LFMC and EWT by a sigmoidal function (Dennison et al., 2003). This index cumulatively sums the difference between precipitation and reference evapotranspiration over a specified time period. The CWBI is functionally very similar to the Keech Byram Drought Index (KBDI, Keech & Byram 1968) used by the National Fire Danger Rating System (NFDRS) in fire danger estimation, but it does not assume a maximum soil water deficit and relies on several meteorological variables to compute reference evapotranspiration instead of only the maximum daily temperature, as the KBDI does. The index is defined as (Dennison et al., 2003):

\[ \text{CWBI}_t = \sum_{t=0}^{T} (P_t - \text{ET}_{0t}) \]  

Where \( t \) is the time interval, \( P_t \) is the precipitation and \( \text{ET}_{0t} \) is the reference evapotranspiration over each interval.

![Fig. 3. LFMC seasonal trends observed in grasslands (top) and shrublands (bottom) for dry and wet years.](image-url)
Reference evapotranspiration was calculated by applying the FAO-56 modified Pennman–Monteith equation (Allen et al., 1998), using incoming solar irradiance, air temperature, vapour pressure and wind speed as input variables. Since dry and wet years should exhibit different CWBI values, this index was used to decide whether to apply the dry or wet year model to a particular year. The CWBI was calculated monthly for each hydrological year from September to April (autumn to early spring), using the data collected by the meteorological station installed at the Cabañeros National Park. Limitation of CWBI computation to mid-spring was twofold: first, to apply the dual model in an operative manner in fire danger rating, a decision about dry/wet years should be made before the critical fire period; and

Fig. 4. Mean CWBI, soil water reservoir and field measured LFMC values at the beginning of the spring season in Cabañeros National Park.

Fig. 5. LFMC–CWBI relationship for grassland (top) and C. ladanifer (bottom).
second, the largest differences in LFMC between dry and wet years are found during the spring.

The CWBI index was calculated from 1998 to 2003 and 2005 (data from 2004 was not available due to a technical problem with our meteorological station). Dennison et al. (2003) limited the index to be positive until the last significant precipitation of the year (>3 mm), however no such constraint was applied in this study. The soil water reservoir was also used in the classification, using an estimated soil water capacity of 200 mm (Gandullo, 1994). To calculate the soil water reservoir, the evapotranspiration was approximated to the ET0 when the precipitation was higher than the ET0 and to the precipitation when it was lower than the ET0.

3.4. Empirical model construction

3.4.1. Adjustment of a function to the seasonal trends in LFMC

LFMC shows seasonal trends with higher values during the spring and a severe decrease during the summer as consequence of the drought that characterizes the Mediterranean climate. Chuvieco et al. (2004) fitted a temporal variable based on the day of the year to the seasonal trends in LFMC for grasslands and shrublands, which was afterwards applied in multivariate regression analysis. Dry years showed a lower contrast in the seasonal trend of LFMC than wet years, both for grasslands and shrubs (Fig. 3). Consequently, in this study, a different function of the day of the year was fitted for each of the two types of hydrological years and vegetation types considered. These functions will uphold the inter-annual variation of LFMC trends. Thus, a harmonic function was fitted to the mean value of the LFMC measured on the field for each plot and period for grasslands and C. ladanifer, the latter being considered representative of the Mediterranean shrubs. This function was named Function of the Day of the year (FD). The adjustment of the FD was based on a nonlinear regression analysis using the following model equation:

\[ \text{FD} = A \cdot \left( \sin\left(\frac{\pi \cdot (\text{DOY} + \phi)}{365}\right) \right) + t \]  

Where:

- **FD** is the function of the day of the year.
- **A** is the amplitude or the range of LFMC values
- **DOY** is the day of the year (from 1 to 365)

### Table 1

<table>
<thead>
<tr>
<th>Species</th>
<th>Type of year</th>
<th>A</th>
<th>(\phi)</th>
<th>X</th>
<th>t</th>
</tr>
</thead>
<tbody>
<tr>
<td>Grasslands</td>
<td>Dry</td>
<td>99.08</td>
<td>55.15</td>
<td>25.97</td>
<td>3.93</td>
</tr>
<tr>
<td>Grasslands</td>
<td>Wet</td>
<td>280.35</td>
<td>67.73</td>
<td>15.82</td>
<td>1.28</td>
</tr>
<tr>
<td>Shrubland</td>
<td>Dry</td>
<td>57.57</td>
<td>61.78</td>
<td>11.72</td>
<td>50.97</td>
</tr>
<tr>
<td>Shrubland</td>
<td>Wet</td>
<td>61.66</td>
<td>63.44</td>
<td>8.8</td>
<td>76.21</td>
</tr>
</tbody>
</table>

### Table 2

<table>
<thead>
<tr>
<th>Species</th>
<th>Type of year</th>
<th>Dry Years</th>
<th>Wet Years</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>R^2</td>
<td>p-value</td>
<td>R^2</td>
</tr>
<tr>
<td>FDgrass</td>
<td>0.97</td>
<td>&lt;0.001</td>
<td>0.99</td>
</tr>
<tr>
<td>Fdshrub</td>
<td>0.83</td>
<td>&lt;0.001</td>
<td>0.94</td>
</tr>
</tbody>
</table>

Fig. 6. Fitting of the Function of the Day of the year to the average LFMC value for grassland and shrubs.
ϕ is the initial phase, which determines the DOY at which the actual maximum LFMC value is reached.

x represents the flatness of the function, which will depend on the water stress.

t is the offset over the Y-axis, which is related to the minimum LFMC value.

### 3.4.2. Multivariate linear regression

The physiological differences between grasslands and shrubs, made it advisable to fit a different model to each species as it was done in the RM. Construction of the empirical model to estimate LFMC was based on a multivariate linear regression analysis. Data spanning from 1996 to 2005 were included in the statistical analysis. Field LFMC values were used as the dependent variable whilst NDVI and ST and FD were the independent variables. Those years for which no meteorological data were available (1996, 1997 and 2004) were classified as dry or wet according to the field measured LFMC values, and then the proper FD was applied. The criterion used in such cases was to classify a year as dry when its mean LFMC during the spring was lower than the mean LFMC of all years minus one standard deviation. A calibration set was built from a random sample of 60% (94 periods)

![Observed vs. estimated LFMC values for grasslands (top) and shrubs (bottom) at the calibration site.](image)

**Table 3**

<table>
<thead>
<tr>
<th>LFMC estimation mode</th>
<th>R² (60%)</th>
<th>p-value</th>
<th>R² (40%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>G*: 27.745 – 1.1 *ST + 293.197 *NDVI + 0.676 *FD</td>
<td>0.83</td>
<td>&lt;0.001</td>
<td>0.93</td>
</tr>
<tr>
<td>S**: 31.773 – 0.476 *ST + 45.810 *NDVI + 0.761 *FD</td>
<td>0.71</td>
<td>&lt;0.001</td>
<td>0.84</td>
</tr>
</tbody>
</table>

G*: Grassland; S**: Shrubland.
of the raw data including data from all years and sampled months, while the remaining 40% (70 periods) were left for validation purposes. Additional validation was carried out at other sites using the data collected in two field campaigns (2000 and 2001); the subsequently derived models were also compared to the RM.

4. Results and discussion

4.1. Classification of dry/wet years

Six hydrological years were used to compute the CWBI and the soil water reservoir, and to classify each year according to its precipitation regime. Fig. 4 shows the mean value of the CWBI, the soil water reservoir and field measured LFMC values at the beginning of the spring season. This period of the year shows higher contrast than the summer season, especially for dry years.

A significant correlation between the CWBI and field collected LFMC was found using an exponential function, both for grassland (R²=0.67, p-value<0.001) and shrubland (R²=0.72, p-value<0.001; Fig. 5).

Two years (1999 and 2005) showed negative values of CWBI and also represented the lowest LFMC values, especially for grasslands. Grasslands are more easily affected by drought than shrubs, the latter having a greater capacity to extract water from the soil. Dennison et al. (2003) working in similar Mediterranean ecosystems found the lowest LFMC values at large CWBI deficits too. The CWBI for 2002 was also negative; however the influence of the available soil moisture reservoir implied that LFMC values were similar to those from years with a positive CWBI value. Despite having a negative CWBI value and low soil water reservoir value, 2002 displayed the second highest LFMC values for grassland, due to the precipitation that occurred during April that year. Therefore, only those years with negative values of CWBI and no soil water reservoir were classified as dry years (i.e. 1999 and 2005) for the subsequent analysis, while the remaining years were considered as normal or wet years.

4.2. Empirical model construction

4.2.1. Adjustment of the FD

Four functions of the day of the year (FD) were built to take into account the seasonal trends of LFMC. These functions were derived from nonlinear regression analysis, for the two vegetation types (grasslands and shrublands) and two hydrological years (dry and wet) considered in this study. The parameters obtained for each FD are presented in Table 1.

Fig. 8. Temporal evolution of estimated and observed FMC values for grasslands (top) and shrubs (bottom).
The derived temporal functions show good fittings to the LFMC trends observed in grasslands and shrublands (Fig. 6). The estimations were better than for the FD of the RM, because of the differences between dry and wet years that were contemplated in the new model. This improvement was clearer for dry years. The agreement between the derived FD and the mean LFMC values was confirmed by the determination coefficients ($R^2$) of each function (Table 2). $R^2$ were also higher for wet years compared to those obtained for dry years, which could be explained because only two dry years were available in the time series. Moreover, the two dry years of 1999 and 2005 displayed different precipitation patterns, the latter being an extremely dry year whereas the drought of 1999 was less severe. Despite the CWBI was lower for 1999 than for 2005, it should be taken into account that the CWBI of the former was computed from September while for the latter it was calculated only from January due to the lack of meteorological data for 2004.

![Graph](image-url)

Fig. 9. Verification of the models applied to other Mediterranean sites. Negative FMC$_{grasslands}$ estimations obtained when applying the model proposed by Chuvieco et al. (2004) were removed from the analysis.
4.2.2. Building the LFMC models

Two empirical models to estimate LFMC were derived based on multivariate linear regression analysis, one for each of the two plant types considered. The differences in LFMC trends between dry and wet years had already been taken into account by applying the FD; subsequently it was not necessary to derive different equations for dry and wet years. Table 3 shows the results obtained using 60% of the sample for calibration and the remaining 40% for verification purposes.

Significant correlations ($p < 0.001$) were obtained both for grassland and shrubland with determination coefficients of 0.83 and 0.71, respectively. Even higher correlation coefficients were obtained for the validation samples, verifying the robustness of the models ($R^2=0.93$ and $R^2=0.84$ for grasslands and shrublands, respectively). Both models were statistically significant at 99% with $p$-values $< 0.001$. The NDVI had a positive relationship with LFMC, while the ST showed a negative relationship. Both results were expected, because plant drying results in a reduction of chlorophyll activity and LAI values, and an increment of the surface temperature due to a reduction of the evaporative fraction.

As for the significance of the independent variables, the FD was significant at 99% in the two models ($p$-value $< 0.001$). The NDVI was statistically significant at 99% for grassland ($p$-value $< 0.001$) yet was significant only at 95% for shrubland ($p$-value $= 0.031$). The lower significance of the NDVI for shrubs compared to grasslands should be related to the lesser effect of plant drying on chlorophyll activity and LAI reduction. The ST was significant at only 95% in both models ($p$-value $= 0.027$ and 0.033 for grasslands and shrublands, respectively), which can be explained because ST was also correlated with FD. The FD was fitted using only those years for which meteorological data were available, subsequently part of the model is still explained by ST.

This is the case in spring when LFMC displays higher variability and therefore the FD correlates less closely with LFMC values, particularly in dry years. For grassland the intercept was not significant ($p$-value $= 0.336$) while for shrubland it was significant at 95% ($p$-value $= 0.047$).

Despite the statistical significance of ST at the 95% level both for grasslands and shrublands, and the fact that the NDVI was only significant at the 95% level for the shrubland model, these variables were kept because they provide better spatial information than FD.

Fig. 7 shows the results of applying the new model (NM) equations to the whole time series data. The new models were able to explain 85% and 76% of the variance within the LFMC data for grasslands and shrublands respectively, with and RMSE of 42.1% (grassland) and 41.18% (shrub). The new equations showed some under-estimation of the higher LFMC values, however within the context of fire danger estimation this is less important than the over-estimation of low values. It was observed that low LFMC values were over-estimated, however it was found that for the lowest shrub LFMC value collected during the study period (LFMC$\text{observed}=44.07$%) the over-estimation was as low as 13.2% (LFMC$\text{estimated}=57.27$%). In the case of grassland the over-estimation of an observed LFMC value of 30% was only by 8.5% (LFMC$\text{estimated}=38.50$%). For LFMC values lower than 30%, grassland can be considered as dead fuel and appropriate methods to estimate dead FMC should be applied (Aguado et al., 2007).

When considering the temporal evolution of LFMC, it was shown that trends are well represented with low deviations and no apparent bias observed (Fig. 8). In the case of grasslands, the greatest differences between estimated and field data were found during the spring, mainly for 2005, due to the high variability that these species show in LFMC values. The new model did not provide negative values except for one sample during 2002 and one soon after the spring season for 2005; these were caused by very low NDVI values. LFMC values for 2005 were within a range that can be considered as dead fuels ($<30\%$) before the end of the spring season and in this case methods to estimate dead FMC should be applied. In the case of shrublands the fit is consistent throughout the years of the time series, showing lower residuals than for grasslands. The highest residuals of all periods were observed at the beginning of the spring of 1999 and 2005 as consequence of some rainfall, which occurred during the previous days.

When applied to other sites in Spain with similar environmental characteristics the new models presented in this paper offered good correlations with $R^2$ values higher than 0.70, both for grasslands and shrublands (Fig. 9). In the case of grasslands, the new model continues the trend of over-estimating low LFMC values. As for shrublands, the regression line was not close to a 1:1 relationship, indicating over-estimation of low LFMC values and under-estimation of high LFMC values. As it occurred at the calibration site, the over-estimation of the lowest LFMC value observed in the validation sites (LFMC$\text{observed}=64.3\%$) was small and comprised only 12.5% (LFMC$\text{estimated}=76.8\%$).

To assess the benefits of the new models compared to the RM, the latter was also applied to the whole time series of available data. Lower determination coefficients and higher RMSE values ($R^2=0.77$, RMSE$=57.53\%$ and $R^2=0.69$, RMSE$=18.19\%$; for grasslands and shrublands respectively) were obtained. The improvement of the new model is more evident when dry and wet years were considered independently (Table 4). The greatest differences were observed for grassland, as it was expected due to its higher sensitivity to moisture variations. It can be seen that the new models exhibit a clear improvement in the determination coefficients, especially for dry years, and a reduction of the RMSE, when compared to the RM. The better performance of the new models made evident the benefits of separating dry and wet years when estimating LFMC for grasslands. No significant differences in the determination coefficients were observed for shrubs, nevertheless the new model presented lower RMSE values both for dry and wet years. The same trends were found in the sites used to spatially validate the models.

5. Conclusions

This paper presented an update of an empirical model previously derived by Chuvieco et al. (2004) to estimate LFMC in Mediterranean areas. The new model was designed for two vegetation types (grasslands and shrublands) as well as two types of hydrological years (dry and wet), based on the spring conditions. The model relied on NOAA/AVHRR imagery and a temporal function that took into account the inter-annual seasonal trends in LFMC. Separation of the data into dry and wet years allowed a more reliable estimation of LFMC, because the seasonal trends in LFMC are affected by precipitation regimes.

The differences in the seasonal trends of LFMC were well modelled by the temporal functions of the day of the year. Moreover, the new models proposed for dry years avoided most of the negative estimations

<table>
<thead>
<tr>
<th>Species</th>
<th>Hydrological year</th>
<th>Model</th>
<th>$R^2$</th>
<th>RMSE</th>
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</thead>
<tbody>
<tr>
<td>Grasslands*</td>
<td>Dry</td>
<td>RM</td>
<td>0.52</td>
<td>81.76</td>
</tr>
<tr>
<td></td>
<td>Dry</td>
<td>NM</td>
<td>0.77</td>
<td>32.94</td>
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<tr>
<td></td>
<td>Wet</td>
<td>RM</td>
<td>0.62</td>
<td>65.88</td>
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<tr>
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<td>Wet</td>
<td>NM</td>
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<td>46.17</td>
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<tr>
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<td>RM</td>
<td>0.76</td>
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</tr>
<tr>
<td></td>
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<td>Wet</td>
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<td></td>
<td>Wet</td>
<td>NM</td>
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<tr>
<td></td>
<td>Dry</td>
<td>NM</td>
<td>0.76</td>
<td>61.34</td>
</tr>
<tr>
<td></td>
<td>Wet</td>
<td>RM</td>
<td>0.68</td>
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<tr>
<td></td>
<td>Wet</td>
<td>NM</td>
<td>0.71</td>
<td>18.57</td>
</tr>
</tbody>
</table>

Negative estimation were not included.
of the previous model. Since only two dry years were found in our time series (1999–2005), the conclusions should be further tested when a longer time series is available with more years of dry conditions.

The CWB1 proved an adequate method for separating dry and wet years based on spring conditions. Additionally, it was shown that CWB1 values were closely related to LFMC, confirming the trends observed by other authors (Dennison et al., 2003). Once a year has been defined as dry or wet, a different model determined by a specific function to account for seasonal variation, should be applied.

The empirical method proposed in this paper has been calibrated and tested on grassland and C. ladanifer. The application of the model should therefore be constrained to areas with similar vegetation types/species in order to obtain a reliable estimation of LFMC. The proposed method relies on variables that are physically related to LFMC. These variables can be easily derived from satellite imagery (NDVI and ST), and standard meteorological stations, the latter providing data to inform the application of the appropriate temporal function. The long time series imagery available for the AVHRR sensor, at low cost and its temporal and spatial resolutions makes it advisable to be used operationally.

Acknowledgements

This work was funded by the Spanish Ministry of Science and Education through the Environment and Climate Change project (Firemap contract-CGL2004-060490C04-01/CLI). We would like to express our gratitude to the Cabañeros National Park authorities and the team involved in the fieldwork. Language assistance from Matthew Leaver is also acknowledged. Comments provided by reviewers are greatly appreciated.

References


