AGRICULTURAL AND FOREST METEOROLOGY 148 (2008) 523–536

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Review

Estimation of live fuel moisture content from MODIS images for fire risk assessment

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ARTICLE INFO

Article history:
Received 15 January 2007
Received in revised form
6 December 2007
Accepted 8 December 2007

Keywords:
Remote sensing
Radiative transfer models
Fuel moisture content
Fire risk assessment
MODIS

ABSTRACT

This paper presents a method to estimate fuel moisture content (FMC) of Mediterranean vegetation species from satellite images in the context of fire risk assessment. The relationship between satellite images and field collected FMC data was based on two methodologies: empirical relations and statistical models based on simulated reflectances derived from radiative transfer models (RTM). Both models were applied to the same validation data set to compare their performance. FMC of grassland and shrublands were estimated using a 5-year time series (2001–2005) of Terra moderate resolution imaging spectroradiometer (MODIS) images. The simulated reflectances were based on the leaf level PROSPECT coupled with the canopy level SAILH RTM. The simulated spectra were generated for grasslands and shrublands according to their biophysical parameters traits and FMC range. Both models, empirical and statistical models based on RTM, offered similar accuracy with better determination coefficients for grasslands ($r^2 = 0.907$, and 0.894, respectively) than for shrublands ($r^2 = 0.732$ and 0.842, respectively). Although it is still necessary to test these equations in other areas with analogous types of vegetation, preliminary tests indicate that the adjustments based on simulated data offer similar results, but with greater robustness, than the empirical approach.

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0168-1923/$ – see front matter
doi:10.1016/j.agrformet.2007.12.005

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1. Introduction

Wildfires are a natural disturbance worldwide, being responsible for an important share of global greenhouse gas emissions (Palacios-Orueta et al., 2005), land use change (Ahern et al., 2001), and soil degradation (Doerr et al., 2006). Fires also have positive feedbacks in the vegetation natural succession and soil properties, but these effects are very much dependent on fire intensity and duration (Johnson and Miyanishi, 2001).

Mediterranean ecosystems have co-existed with fires for millennia, since summer drought makes them prone to fire ignition and therefore can be considered a natural phenomenon (Naveh, 1989). However, recently the natural fire regimen has changed, increasing the harmful effects of wildland fires, both on environment and society. Climate change has not been widely reported as a key issue in the changes in the Mediterranean fire regime but land use changes as a result of economic transition from agricultural to industrial societies first, and then the increase in tourist-related land uses are most commonly recognized as the main drivers of the recent fire activity in the region (Vega-Garcia and Chuvieco, 2006). Therefore, the growing urbanization of forested areas has increased too the potential damage of fire on the wildland–urban interface (Leone et al., 2003).

New strategies for earlier fire prevention and extinction are required to handle these new threats and to improve the management of the Mediterranean forests. Wildfire risk evaluation systems provide an integrated approach for managing resources at stake and reducing the negative impact of wildland fires. These systems should include a wide range of factors that are related to fire ignition, fire propagation and fire vulnerability (Chuvieco et al., 2003b). Fuel moisture content (FMC), defined as the proportion of water over dry mass, has been the most extended measure of fire ignition and fire propagation potential, and it has been widely used for fire danger assessment (Blackmarr and Flanner, 1968; Fosberg and Schroeder, 1971; Paltridge and Barber, 1988; Pompe and Vines, 1966; Trowbridge and Feller, 1988; Viegas et al., 1992), since the fuel water content has a clear impact on ignition delay and fire rate of spread (Nelson, 2001). FMC is also critical for planning of prescribed burns (Baeza et al., 2002) which are growingly considered a critical aspect of integrated fire management. Finally, it has also been related to burning efficiency, which is a critical component of fire emission models (Chuvieco et al., 2004a). In addition to fire-related applications, the estimation of plant water content is an essential input of vegetation productivity models (Boyer, 1995), and to improve water management in irrigated agriculture (Sepulcre-Cantó et al., 2006).

Direct estimation by field sampling provides the most accurate method to obtain FMC, commonly using gravimetric methods, namely the weight difference between fresh and dry samples (Lawson and Hawkes, 1989). However, this approach is very costly and the generalization to regional or global scales results unfeasible. The use of meteorological indices is widespread, since they provide an easy spatial and diachronic estimation of FMC (Camia et al., 1999), but they also present operational difficulties since the weather stations are often located far from forested areas and may be scarce in fire prone regions. Furthermore, these estimations are reasonably well suited for dead fuels, because their water content is highly related to atmospheric conditions. However, in live fuels, species physiological characteristics and adaptation to drought imply a great diversity of moisture conditions with the same meteorological inputs (Viegas et al., 2001).

FMC estimation of live fuels can also be based on remote sensing methods, since FMC variations affect fuel reflectance and temperature. The monitoring of grass curing from satellite images was proposed by Burgan and collaborators (Burgan and Hartford, 1993), within the potential revisions of the National Fire Danger Rating System (NFDRS). A further elaboration of this concept led to the use of greenness indices (defined as the relative change in vegetation index values with respect to time series maximum and minimum) as an estimation of dead versus live fuels proportion to compute fire danger potential (Burgan et al., 1998). Later, both empirical (Chen, 2005; Chuvieco et al., 2004b; Paltridge and Barber, 1988; Roberts et al., 2006) and simulation approaches (Jacquemoud and Ustin, 2003; Riaño et al., 2005; Zarco-Tejada et al., 2003) were developed to estimate FMC from remote sensing data. The empirical methods are commonly based on statistical fitting between field-measured FMC and reflectance data. They have a known accuracy and are simple to compute. However, those empirical relationships are sensor and site-dependent, and therefore difficult to extrapolate to regional or global scale studies due to differences in leaf and canopy characteristics (Riaño et al., 2005) or sensor calibration and observation conditions.

Estimation of water content from simulation approaches has frequently been based on inversion of radiative transfer models (RTM). Since these models are based on physical relationships that are independent of sensor or site conditions, they should be more universal than empirical fittings. However, the selection and parameterization of RTM is far more complex than empirical models, since they are based on assumptions that may not accurately resemble those found in nature, especially when complex canopies are involved (Liang, 2004). Most studies based on RTM have found that the equivalent water thickness (EWT), defined as the amount of water per leaf area, can be retrieved from reflectance data, since it represents the water absorption depth of leaves (Ceccato et al., 2002; Datt, 1999). However, the FMC is more difficult to estimate from reflectance measurements, since it does not only depend on water absorption, but also on the changes in dry matter as a result of leaf drying. Sensitivity analysis based on a wide range of conditions has found potential for FMC retrieval from reflectance measurements (Bowyer and Danson, 2004), providing that the dry matter content can also be estimated (Riaño et al., 2005).

The main objective of this study was to compare the performance of empirical and RTM approaches to derive FMC of Mediterranean species from satellite reflectance measurements. The final goal was to derive an operational estimation that could be integrated with other factors of wildland fire risk.

2. Methods

The general scheme of the method developed in this paper is presented in Fig. 1. The empirical approach was derived from multivariate linear regression (MLR) analysis between field-collected FMC data and reflectance values derived from the moderate resolution imaging spectroradiometer (MODIS). The field samples were divided in two sets: 60% for calibrating the model and the remaining 40% for the validation. Two different models were built for grasslands and shrublands. The simulation approach was derived from RTM that were parametrized using field data, auxiliary information derived from MODIS products and the knowledge of the type of canopy architecture that define which RTM is appropriate (Combal et al., 2002). Once the simulated reflectance values for grasslands and shrublands were obtained for the whole solar spectrum, they were convolved to the MODIS spectral wavelengths and band widths. Finally, separate MLR models between the simulated reflectances and the grassland and shrubland FMC values were built, in a similar way to the empirical method. Those equations were applied to the MODIS data for the same validation dataset as the empirical model to compare the performances of both approaches.

2.1. Field sampling

A field campaign has been carried out by our research group since 1996 to the present in the Cabañeros National Park (Central Spain; Fig. 2) to collect samples of different Mediterranean species for field FMC estimation. Three plots of grassland and two of shrubland (*Cistus ladanifer* L., *Rosmarinus officinalis* L., *Erica arborea* L. and *Phyllirea angustifolia* L.) sized 30 m × 30 m, were collected in gentle slopes (<5%) and homogeneous patches. For this paper, FMC values of *C. ladanifer* L. were selected as representative for shrubland plots since it is very common in Mediterranean siliceus areas. It appears in a 29.79% of the study area covering a radius of 100 km from the National Park being the dominant species in more than 6% versus less than 16% of appearance and 1% of dominance of the other three species together in the same area. In addition to this, it is a typical pioneer species that regenerates easily by seeds after diverse types of handlings and disturbances (Nuñez Olivera, 1988), so it is the primary colonizer in areas with recurrent wildfires, which are of special interest in this study.

The sampling protocol followed standard methods described in Chuvieco et al. (2003a) and was repeated every 8 days during the spring and summer seasons from 1996 to 2002 and every 16 days from 2003 on. For this paper, FMC measurements taken from 2001 to 2005 have been used to correspond with the temporal series of the MODIS images.

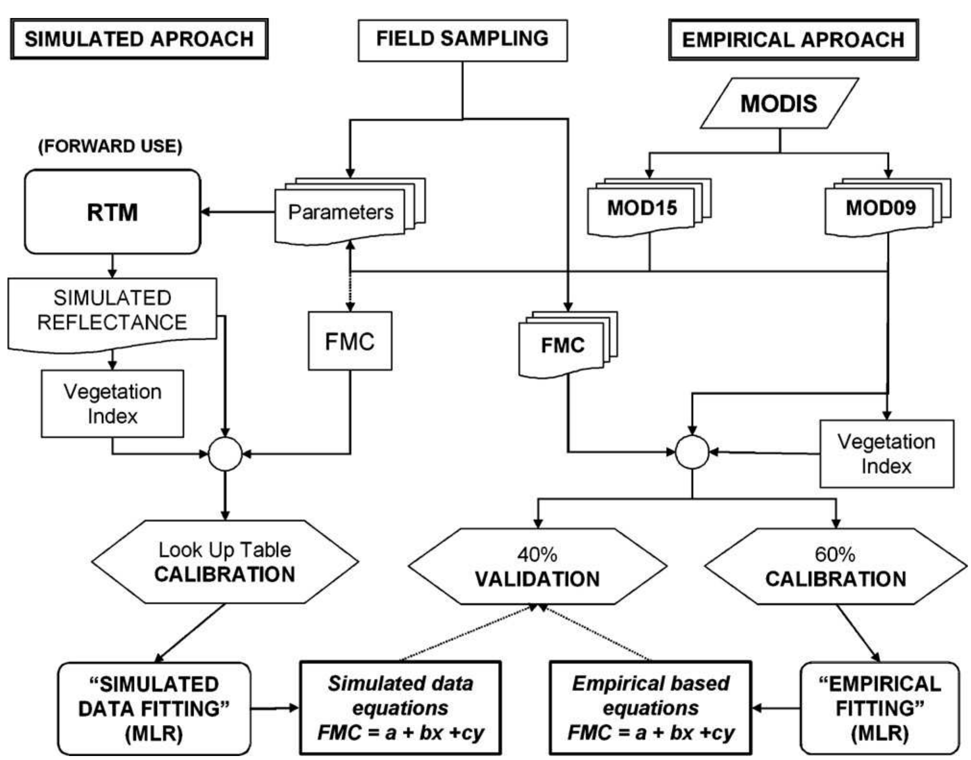

Fig. 1 – Methodological flowchart.

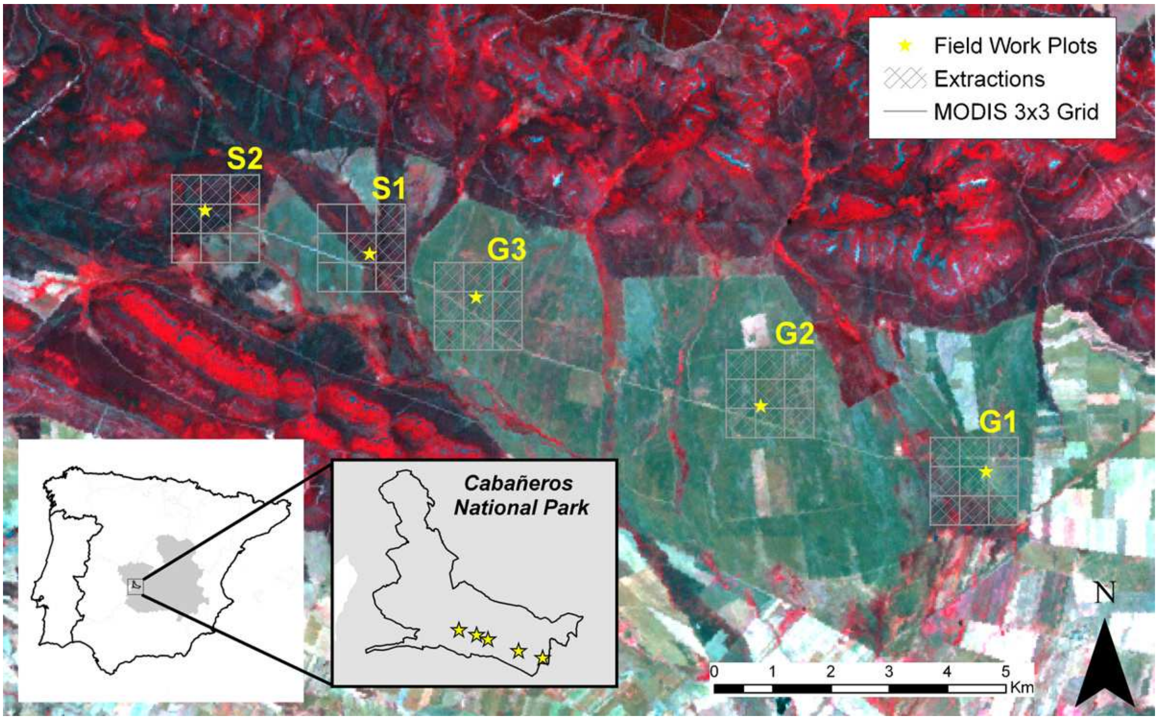

Fig. 2 – Map of Spain showing the location of Cabañeros National Park, as well as a false color composite Landsat image showing the midpoint of the shrubland (S1 and S2) and grassland (G1, G2 and G3) plots used in this analysis. The grey boxes indicate the 3 × 3 MODIS grid (1.5 km × 1.5 km) centered at the plots. Shaded boxes indicate the window adapted to the shrub shape plot.

FMC was computed from the difference of fresh and dry weight as following:

$$\mathrm{FMC}\,(\%) = \frac{W_f - W_d}{W_d} \times 100; \tag{1}$$

where W_f is fresh weight of leaves and small terminal branches (in the case of shrub species) or the whole plant (in the case of grassland), and W_d is dry weight, after oven drying the samples for 48 h at 60 °C.

After 2004, FMC field sampling incorporated the collection of variables that are critical for running the RTM at leaf level, such as dry matter content (DM), equivalent water content (EWT) and chlorophyll content (Ca + b).

DM and EWT were computed following:

$$\mathrm{DM}\,(\mathrm{g\,cm^{-2}}) = \frac{W_d}{A}, \tag{2}$$

and

$$\mathrm{EWT}\,(\mathrm{g\,cm^{-2}}) = \frac{W_f - W_d}{A} \tag{3}$$

where W_f and W_d are the same as in (1) and A is the leaf area.

C. ladanifer L. leaf area was measured with an image analysis Delta system (Delta Devices LTD, Cambridge. England). Ca + b was measured by means of destructive sampling and measurement of leaf concentration in laboratory with the dimethyl sulfoxide (DMSO) method and spectrophotometric readings, according to Wellburn (1994). For grasslands, DM and Ca + b measurements were provided by a field ecologist working in similar environments (Valladares, personal communication). Spectral soil reflectance was also measured with a GER 2600 (GER Corp., Millbrook, NY) radiometer to use as an input at canopy level model.

2.2. *MODIS data*

Two standard products of the MODIS program were chosen for this study: the MODIS/Terra surface reflectance (MOD09A1) and the MODIS/Terra leaf area index (LAI) and fraction of photosynthetically active radiation (FPAR) (MOD15A2). The first is an 8-day composite product of atmospherically corrected reflectance for the first seven spectral bands of the MODIS sensor at a spatial resolution of 500 m (Fig. 3). This product includes ancillary information, such as sun and sensor angles (Vermote and Vermeulen, 1999). The standard MOD15A2 product was selected to take into account the strong effect of LAI variations on reflectance as well as to parametrize the RTM. This product is generated daily at 1 km spatial resolution and composited over an 8-day period based on the maximum value of the FPAR for that period (Knyazikhin, 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/) and reprojected from sinusoidal to UTM 30 T Datum European 1950 (ED50) using nearest neighbour interpolation resampling. MOD15A2 data were

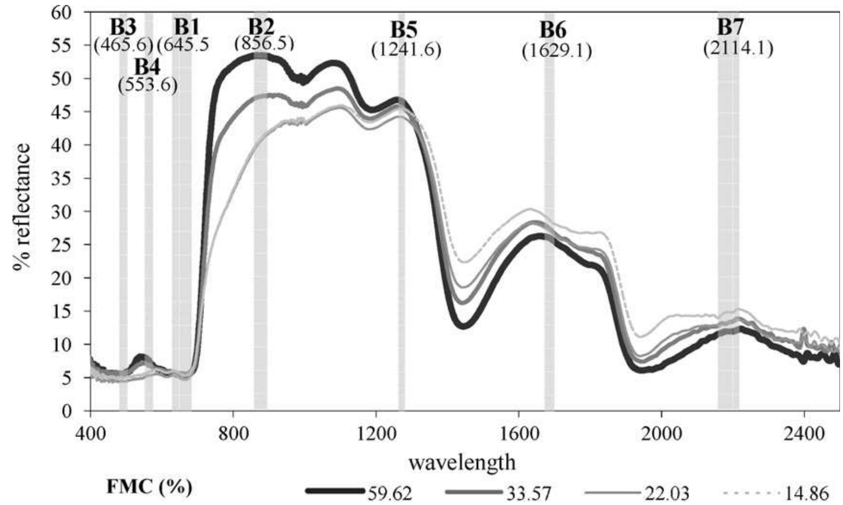

Fig. 3 – Example of reflectance spectrum (400–2500 nm) of different FMC values for *C. ladanifer* L. measured with GER 2600 under laboratory experimentation showing location of MOD09A1 band regions (grey bands) with their central wavelength (between brackets).

resampled to 500 m to match the resolution of the MOD09A1 product using the same interpolation algorith. The values of a given plot for comparing with the field data were extracted from each composited image using the median value of a 3×3 pixel kernel located at the center of the field plot. A 3×3 window was used in order to reduce the potential noise due to residual atmospheric effects and georeferencing errors. In the case of shrublands, extraction windows were adapted to the shape of shrub patches to avoid including mixed pixels (Fig. 2). To verify this approach the coefficient of variation (CV) was computed for reflectances for a Landsat image (30 m $\times$ 30 m pixel size) within the extraction windows. The CV decreased from 0.052 and 0.255 of the 3×3 windows in the near infrared band (NIR) and the short wave infrared (SWIR) bands, respectively, to 0.050 and 0.195 with the adapted window. The extractions of reflectance data of each pixel were derived from the 8-day composite that had a closest selected day to the field collections.

A wide range of vegetation indices were calculated to be included as independent variables in the empirical MLR model (Table 1). Only one form of the NDII using band 6 (1628–1652 nm) was calculated based on previous studies which show stronger correlations between this band and field measured FMC values than other MODIS bands in the SWIR region (Roberts et al., 2006; Yebra et al., 2005).

The first five indices in Table 1 measure greenness variations, which are only indirectly related to leaf water content. The other indices included in Table 1 are more directly related to water content, by combining water absorption in the SWIR wavelengths with other bands that are insensitive to water content (Fourty and Baret, 1997). Although greenness indices do not include water absorption bands, they can be used as an indirect estimation of water content, since moisture variations affect chlorophyll activity, leaf internal structure and LAI of many Mediterranean plants (Bowyer and Danson, 2004). In this sense, as the plant dries, changes in leaf internal structure cause a decrease in the reflectance in the NIR and an increase in the visible region, as a result of reducing photosynthetic activity and LAI values. However, this relation cannot be generalized for all ecosys-

Table 1 – Spectral indices calculated for MODIS including their shortened acronym, mathematical formulation and citation

Index	Formula	Reference
"Normalized Difference Vegetation Index"	$\mathrm{NDVI} = \dfrac{\rho_2 - \rho_1}{\rho_2 + \rho_1}$	(Rouse et al., 1974)
"Soil Adjusted Vegetation Index"	$\mathrm{SAVI} = \dfrac{\rho_2 - \rho_1}{\rho_2 + \rho_1 + L}(1 + L)$	(Huete, 1988)
"Enhanced Vegetation Index"	$\mathrm{EVI} = \dfrac{2.5(\rho_2 - \rho_1)}{\rho_2 + 6\rho_1 - 7.5\rho_3 + 1}$	(Huete et al., 2002)
"Global Environmental Monitoring Index"	$\mathrm{GEMI_I} = eta(1 - 0.25eta) - \dfrac{\rho_1 - 0.125}{1 - \rho_1}$ $eta = \dfrac{2(\rho_2^2 - 1.5\rho_2 + 0.5\rho_1)}{\rho_2 + \rho_1 + 0.5}$	(Pinty and Verstraete, 1992)
"Visible Atmospheric Resistant Index"	$\mathrm{VARI_i} = \dfrac{\rho_4 - \rho_1}{\rho_4 + \rho_1 - \rho_3}$	(Gitelson et al., 2002)
"Normalized Difference Infrared Index"	$\mathrm{NDII_6} = \frac{\rho_2 - \rho_6}{\rho_2 + \rho_6}$	(Hunt and Rock, 1989)
"Normalized Difference Water Index"	$\mathrm{NDWI} = \dfrac{\rho_2 - \rho_5}{\rho_2 + \rho_5}$	(Gao, 1996)
"Global Vegetation Moisture Index"	$\mathrm{GVMI} = \dfrac{(\rho_2 + 0.1) - (\rho_6 + 0.02)}{(\rho_2 + 0.1) + (\rho_6 + 0.02)}$	(Ceccato et al., 2002)

tems because, for example, variations on chlorophyll content can also be caused by plant nutrient deficiency, disease, toxicity and phonological stage (Ceccato et al., 2001).

2.3. Generation of simulated reflectances

The use of RTM in remote sensing analysis can follow two different approaches: forward and backward simulation. The former is based on changing input parameters and analyzing the effects on the simulated reflectance to assess the importance of each input parameter in the different spectral wavelengths. The backward simulation, also named inversion, estimates which set of input parameters produces a simulated reflectance more similar to a particular observed reflectance. The concept of ''similar'' spectrum is commonly formalized in RTM inversion approaches using the merit function, which implies minimizing the differences between the observed and modeled reflectances:

$$\chi^2 = \sum_{i=1}^{n}[\rho_i - M(\Theta, X_i)]^2 \tag{4}$$

where χ is the difference between the observed reflectance (ρ) and the modeled reflectance $M(\Theta, X)$, for a certain set of input parameters (Θ, X), being X the value to be estimated, and n the number of spectral wavelengths of the input image.

The inversion process can be achieved through iteratively running the model until finding a spectrum (and its corresponding set of parameters) that closely matches the reflectance values extracted from satellite data. Alternatively, the model can be run in advance and which of the simulated reflectances is more similar to the observed spectrum can be determined later. In both cases, once the most similar simulated spectrum is found, the set of parameters that generated that spectrum is considered a good estimation of vegetation conditions of the area where that satellite observation came from (Zarco-Tejada et al., 2003).

The second approach is usually designed as the generation of a look up table (LUT) (Liang, 2004), and it is the most commonly used since it is quicker, provides a control scenario on the input parameters to be searched for (Combal et al., 2002) and allows the identification of ambiguous situations where there are several set of input parameters which can produce a modeled result that agrees with the observations within a tolerance (Gobron et al., 2000; Saich et al., 2003).

The LUT approach was selected for this paper. A LUT includes the output of running the RTM for the different simulation scenarios ($M(\Theta, X)$ as stated in (4)). Therefore, the inversion process does not need to run the model for each pixel of the image, but rather it can focus on finding which of the modeled spectrum is most similar to an observed pixel reflectance, most commonly using a merit function of ''spectral similarity'' based on the quadratic distance (as formulated in (4)). Alternatively to this search, relationships over the modeled spectrums and a corresponded key biophysical parameter, using neural network or genetic algorithms (Fang and Liang, 2003) can be built. For this study, a MLR between the simulated reflectance and their associate FMC in the LUT was used, in a similar way as the model derived for empirical data.

Spectral reflectances between 400 and 2500 nm were simulated for different FMC values by linking two well-known RTM: the PROSPECT leaf model (Jacquemoud and Baret, 1990) and the SAILH canopy model (Verhoef, 1984). PROSPECT simulates reflectance and transmittance of a leaf by considering it as a set of N stacked layers with several absorption components (Ca + b; DM and EWT). SAILH is a model that simulates canopy reflectance from the output of the PROSPECT model (leaf reflectance and transmittance) plus a set of variables affecting the canopy. The main ones are the leaf area index (LAI), leaf angle distribution function (LADF), the hotspot parameter, which is a relation between leaf size and canopy height, the soil substrate (soil reflectance) and viewing and illumination conditions (Sun and view zenith angle, relative azimuth sensor-sun angle and atmospheric transmissivity).

The PROSPECT–SAILH models were run to create a LUT for a wide set of FMC values. For each simulation case, the FMC was computed as a ratio of EWT and DM, two of the input parameters of the PROSPECT model. Input parameters for running these models are included in Table 2. They were derived from our field sampling and literature review. A random noise factor of the size of half a step of the simulation was introduced in the simulation step to cover the variation space of the model and therefore avoid gaps with fixed values.

Since the set of simulations might include unrealistic combinations of input parameters, a filter criterion was applied to eliminate those simulations which would not be likely to occur. In Mediterranean conditions, annual grasses escape drought by reducing their vital cycle and when grass dries it tends to reduce leaf cover as a result of loosing turgidity and the consequent leaf curling (Valladares, 2004). On the other hand, shrubs frequently adapt to the summer condition by reducing leaf area and increasing non-photosynthetic material (Valladares, 2004), and therefore increasing DM. For all above mentioned, either the lowest LAI or highest DM values are unlikely to combine with the highest FMC in Mediterranean grasslands or shrublands, respectively. Therefore, field observations were used to derive two linear relations, a positive one between FMC and LAI for grasslands, and another negative between FMC and DM for shrublands (Fig. 4) and were used for filtering out some of the simulations. The cases that exceeded a 10% of the maximum or minimum residual of the regression fitting were eliminated. This 10% margin of error was arbitrary added in order to take into account the possibility that other sites, with other species, have different relations. It must be better determined by measurements at other sites.

The final LUT included 1331 spectra for grasslands and 503 for shrublands. The simulated spectra were convolved to the seven MOD09A1 reflectance bands, by means of sensor response functions, to be used as input bands for the MLR model. Additionally, the same vegetation indices considered in the empirical model were computed as well (Table 1).

2.4. Data analysis

The empirical modeling was based on stepwise multivariate linear regression analysis (MLR). Forward inclusion with 0.08 (in) and 0.1 (out) significance levels were selected (SPSS, 2004). Two different models were used for FMC estimation, one for

Table 2 – Input parameters for the PROSPECT–SAILH simulations

Model	Parameter	Grassland			Shrubland		
		Min.	Mx.	Step	Min.	Mx.	Step
Prospect	N	1.25	2.5	0.5	1.25	2.5	0.5
	DM (g cm^{-2})	0.002	0.007	0.001	0.02	0.04	0.003
	EWT (g cm^{-2})	0.0001	0.017	0.0003	0.012	0.03	0.002
	Ca + b (μg cm^{-2})	20	20	–	45	45	–
Sailh	LAI	0.5	2	0.6	0.5	3	0.6
	Hotspot	0.001	0.001	–	0.008	0.008	–
	ts	27	51	16	27	51	16
	tv	5	5	–	5	5	–
	psr	−30	−30	–	−30	−30	–

SAILH LADF parameter was fixed to erectophile and plagiophile for grasslands and shrublands, respectively. The soil spectrum was that one measured in Cabañeros National Park. Sun zenith angle (ts), sensor zenith angle (tv), and relative azimuth sensor-sun (psr) in degrees.

grasslands and one for shrub species, using *C. ladanifer* L. as a representative species. Average values of the three plots of grasslands on one hand, and the two plots of *C. ladanifer* L. on the other, were used for building the models. In this way, the FMC values are more representative of the coarse pixel size of the MODIS images. There were 66 sample periods, which were randomly divided into two groups, 60% for the calibration of the empirical models ($n = 40$) and 40% for the validation ($n = 26$). To check the robustness of the relationships, several 60% random samples were obtained to derive the linear models. Dry and wet years were included in each group, which assures greater significance of the results.

Two additional linear regression models for grassland and shrublands were built with the simulated reflectance and FMC values using stepwise forward MLR selection. Model calibration for each vegetation class was based on all of the simulated

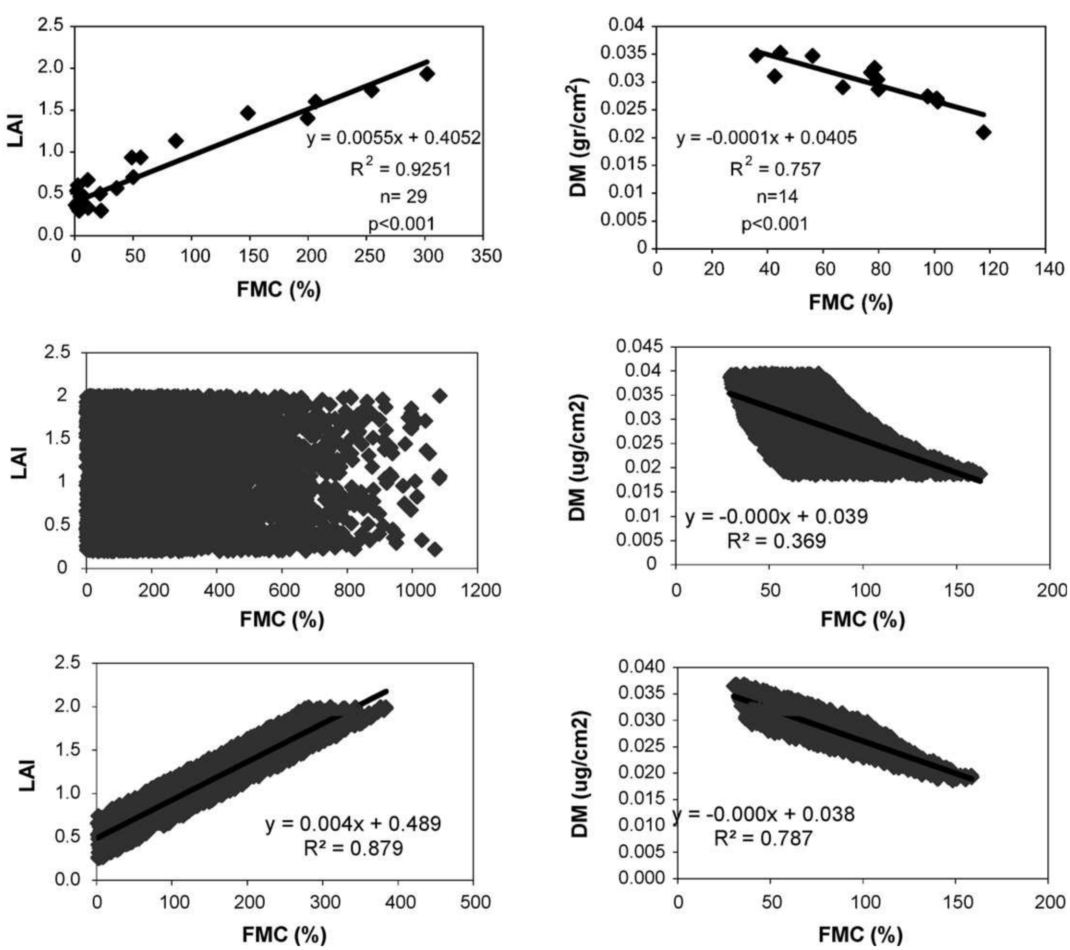

Fig. 4 – Scattergraphs of relations between FMC and LAI (grasslands), and DM (shrubland) for field data observations (top), initial LUT (center) and final LUT (bottom). These models were derived exclusively from field data, only periods with LAI and DM field data were considered.

dataset so in this case the sample was much higher than for empirical data, since there were many more simulations than field sampling periods. To better compare results with the empirical data, the validation of these models was performed with the same cases used to assess the empirical models. In this case, the independent variables for the MLR were the MODIS simulated reflectances, the spectral indices derived from them (extracted from the LUT) as well as the LAI values for the grassland model and the DM values for the shrublands model. The decision to include LAI and DM in the MLR analysis was based on previous experience with RTM iterative inversion software (Rueda, 2001), which only offered good results when LAI and DM were fixed. In this sense, if the FMC models are calibrated using LAI or DM as independent variables they will account for variation in these two parameters and ancillary data can be used later on to fix those values, in the same way that they were fixed in the iterative algorithm, and therefore the inversion is constrained.

For the validation with the same sample as the empirical models, the LAI values were extracted from the MODIS standard LAI product (MOD15A2), and the DM was estimated from our seasonal field measurements. As a starting approach a simple model based on just two average DM values for spring (0.026 g cm^{-2}) and summer (0.032 g cm^{-2}) were used. Similarly to the empirical approach, once the model was calibrated, several 60% random samples were obtained to check the robustness of the relationships.

The accuracy of the empirical and simulated models was measured from the determination coefficient (r^2), the slope of the relationship between observed and predicted values and the root mean square error (RMSE), which summarize the difference between the observed and predicted FMC. This RMSE was decomposed into systematic (RMSEs) and unsystematic (RMSEu) portions (Willmott, 1982). The latter takes into account errors caused by uncontrolled factors, while the former 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.

3. Results

3.1. FMC evolution versus reflectance data

Temporal trends in FMC values and several MODIS bands are shown in Fig. 5. FMC values of grasslands show a large oscillation between the spring and summer seasons. The former had values in the range of 250–300%, while the latter presented FMC values below 30%, which can be considered as dead matter. This cycle in FMC values was clearly observed too in the MODIS reflectance data, although with maximum FMC values corresponded with minimum reflectance values in the band 1 (620–670 nm), 6 (1628–1652 nm) and 7 (2105–2155 nm) wavelength, and maximum in band 2 (841–876 nm). The spring/summer variation of FMC values in 2005 was lower than in other years, because of the exceptional dry conditions. However, the reflectance variation is similar to other years, with the exception of band 2, which shows an increase in reflectance instead of a decrease in summer time. The reflectance values of April 2005, practically match those FMC values at the beginning of June for the rest of the years.

Less seasonal oscillation is observed for FMC values of shrublands, which range between 60% and 120% most years. The exception is again 2005 with very low FMC values. That year, the FMC contents were below 100% in the spring season, reaching values below 60% in summer time. FMC had similar effects on reflectance bands 1, 6 and 7 as in the grassland case but seasonal reflectance variations, just like FMC one, were much smaller in amplitude. These lower variations were reflected in the regression analyses that follow. For shrublands, NIR band (2) did not show a clear correspondence to FMC variations.

Table 3 shows Pearson r coefficients between the temporal evolution of FMC and MODIS reflectance bands. Bands 1, 6 and 7 had significant correlations both for grasslands ($p < 0.001$) and shrublands, although in this case with lower significance level ($p < 0.005$). Band 2 was significant for grassland ($r = 0.54$, $p < 0.001$) while it was uncorrelated with shrubland FMC ($r = 0.0078$). The spectral vegetation indices showed very good correlations for grasslands ($r > 0.62$), and lower for shrublands ($0.32 < r < 0.81$). The red/NIR indices (EVI, NDVI, SAVI) provided a sound estimation of FMC for grasslands, while those based on the NIR/SWIR space (NDII, GVMI, NDWI) offered better results for shrublands, although NDVI still provides high r values for shrublands. The VARI index, which is a combination of the blue–green–red reflectance, provided the best correlation for *C. ladanifer*, but offered the lowest for grasslands, being the only index with higher correlations for shrubs than for grasslands.

3.2. Correlations between simulated reflectance and FMC

The highest coefficients were observed for those bands located in the SWIR (bands 6 and 7, Table 3). Bands 1 (red) for grassland and 2 (NIR) for shrublands had also a high r coefficient. The latter was opposite to the empirical data, which did not show a significant relationship for band 2. Band 5 (1230–1250 nm) offered better correlations for the simulated than for the observed reflectances. Similarly to the empirical approach, shrubland correlations were generally lower than for grasslands. The spectral indices computed for simulated data provided similar results as those observed for empirical data, although the performance of red/NIR indices for grasslands was less important than for the indices based on the NIR/SWIR. Contrary to the empirical data, the VARI worked better for grasslands than for shrublands.

3.3. Performance of empirical and simulation results

Table 4 shows the variables selected for the MLR empirical models with the different random samples selected. For models derived from empirical data, NDVI was always selected as the most explicative variable for grasslands, and accounted for almost 90% of input variance. The r^2 determination coefficients were similar in the four runs of the model, but the slopes and constants of the equations as well as the standard errors of the estimation (S.E., standard deviation of the error) changed. The selected model (identified as 0 in Table 4) had an S.E. of 30.1%. For shrublands, the r^2

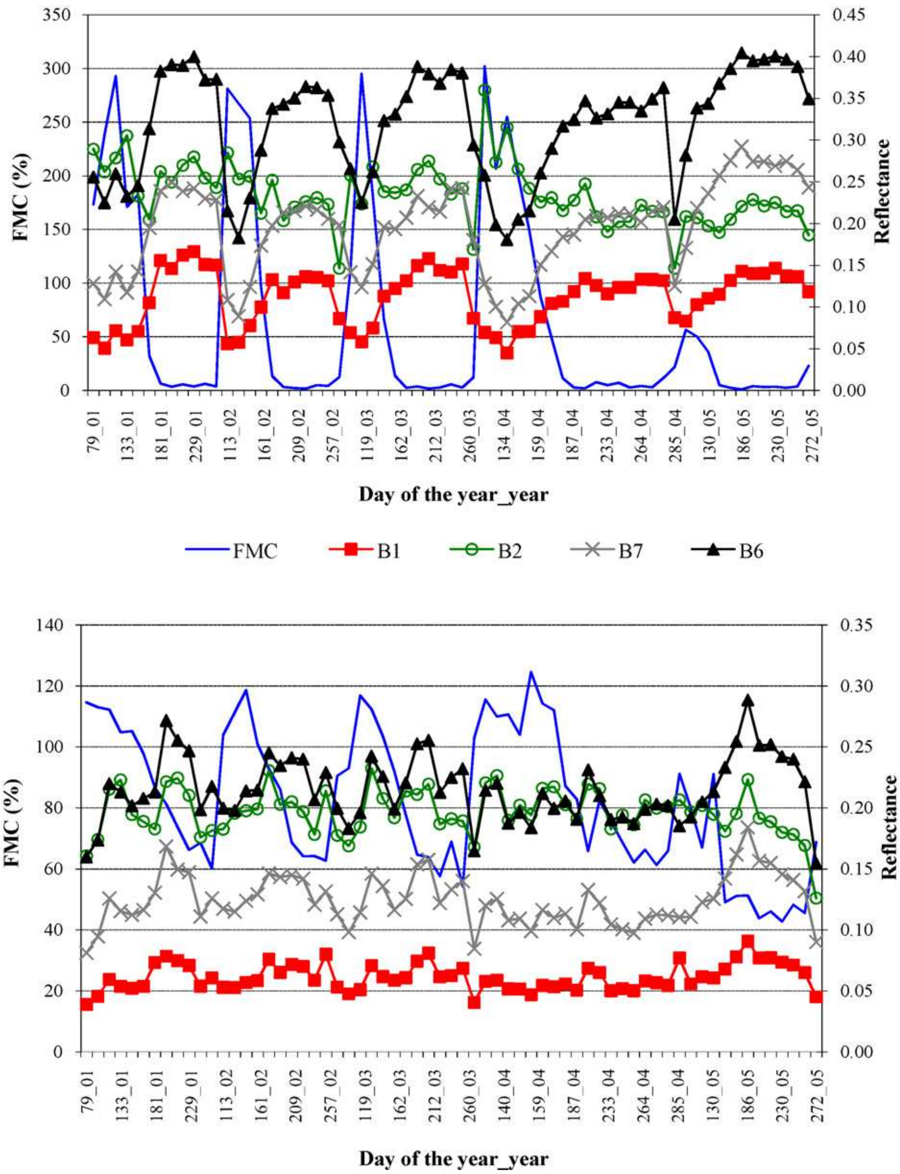

Fig. 5 – Temporal evolution of FMC and MODIS bands 1, 2, 6 and 7 reflectance in the study area for grasslands (top) and shrublands (bottom).

determination coefficients of the MLR estimations were lower than for grasslands, with values between 0.67 and 0.73. The S.E. of the calibrated model was 17.5%. Variables selected were VARI and GVMI, the former accounted for most of the explained variance. As in the case of grasslands, the differences in models by varying randomly the input cases were clearly observed, with notable changes in slopes, constant and S.E.

Models derived from the simulation data show a different behaviour from those generated from empirical data (Table 5). The selected variables were in greater correspondence with the spectral water absorption features. For grasslands, the LAI and the NDII values were selected, but not the NDVI or other red/NIR index. For the shrublands, DM PROSPECT parameter and GVMI were selected. It was observed that choosing randomly 60% cases for the calibration produced slight changes in the models (Table 5). Total determination coefficients were similar to the models generated from empirical data, but standard errors were lower for both grassland (29.5%) and shrubland (12.6%).

The validation of the empirical and simulated data models was carried out with the remaining 40% of the field-FMC measures. In this case, the model inputs were MODIS reflectances in both the empirical and the simulated model, since the simulation was only used to calibrate the model, but the validation was performed with real data. This was also the case for the LAI and DM values, as previously mentioned.

Similar determination coefficients were found for the empirical and simulated data model in both grassland and shrublands (Table 6). The RMSE of the grassland model was higher for the empirical than for the simulated data but the ratio of estimated versus observed FMC values (slope) was quite similar and close to 1 for both generated grasslands models. These RMSE values were computed after negative estimations, which may occur during the driest periods of the

Table 3 – Pearson correlation coefficients between FMC and MODIS-derived data for simulated (SIM) and observed (OBS) data

Pearson	Grassland		Shrubland	
	FMC_{OBS}	FMC_{SIM}	FMC_{OBS}	FMC_{SIM}
B3	**−0.725**	**−0.621**	−<u>0.428</u>	**−0.431**
B4	**−0.680**	**−0.195**	−0.328	**−0.169**
B1	**−0.816**	**−0.710**	**−0.532**	**−0.440**
B2	**0.540**	**0.215**	0.078	**0.698**
B5	**−0.241**	**−0.637**	−0.226	**−0.197**
B6	**−0.768**	**−0.799**	−<u>0.421</u>	**−0.552**
B7	**−0.771**	**−0.793**	−<u>0.427</u>	**−0.503**
$NDII_6$	**0.887**	**0.902**	**0.606**	**0.710**
NDWI	**0.859**	**0.915**	**0.482**	**0.751**
$GVMI_6$	**0.890**	**0.887**	**0.604**	**0.688**
EVI	**0.945**	**0.721**	0.421	**0.760**
GEMI	**0.896**	**0.554**	0.324	**0.772**
VARI	**0.623**	**0.812**	**0.810**	**0.517**
NDVI	**0.952**	**0.792**	**0.678**	**0.590**
SAVI	**0.933**	**0.788**	**0.541**	**0.645**
Samples, n	40	2270	40	503

Bold numbers refer to significant correlations at $p < 0.001$. Underlined are significant at $p < 0.005$.

summer season, were removed. The RMSEu portion of the residual error was higher than the RMSEs for both simulated and empirical datasets. Regarding the shrublands, the empirical data-derived model showed a closer to 1 slope and a lower RMSE than the model derived from the simulated. This later model has a RMSEs higher than the RMSEu.

Fig. 6 shows the temporal trends observed and estimated for the two different models in both grasslands and shrublands. Both the empirical and simulated data model provide better fittings for grasslands variation than for shrublands, where tendencies to overestimation (empirical data model) and underestimation (simulated data model) were observed, especially during the summer period. In the driest year of our study series (2005) grasslands FMC was poorly estimated by the empirical model, while the model based on simulation data was closer to measured values in the spring season (day 111). On the contrary, from the later spring (day 130) onwards, the empirical model performed better than the simulated data model.

4. Discussion

This paper has compared the performance of empirical versus simulated reflectance data for estimating live FMC values. The pros and cons of each approach may be summarized in Table 7. Empirical models, which have been extensively used in remotely sensed applications, generally provide an accurate estimation of the target variable, but are very costly to generate and have only local application. In the case of FMC estimation, empirical models can be generalized by using a wider set of input data, but it would imply an extensive field sampling effort.

Estimations based on simulated data from RTM are a sound alternative to empirical approaches, providing a more physical basis to understand observed relationships. However, they are difficult to parameterize and have assumptions that are not always found in nature. They also present uncertainties in the inversion mode, since very similar reflectances can be derived from a different set of input parameters, which is the well-known ill-posed inverse problem (Garabedian, 1964). Additionally, the physical models do not take into account ecophysiological relations, and therefore they might provide poor estimations when unrealistic combinations of input parameters are considered. Finally, the noise associated with the sensor and data processing (radiometric calibration and atmospheric correction) and illumination effects increase the uncertainties of the inversion process (Combal et al., 2002).

This paper has shown a simple inversion technique based on MLR to retrieve FMC from MODIS data. This estimation has been compared to traditional empirical models in terms of accuracy and robustness.

The Pearson coefficient analysis between FMC values and vegetation indices carried out before the MLR analysis showed that all the red/NIR indices except GEMI correlated with grasslands FMC stronger than NIR/SWIR. This might be due to the fact that GEMI breakdowns with respect to soil noise at low vegetation covers (Qi et al., 1994), which occurs mainly on summer time. On the other hand, NDVI was the only red/NIR index which correlated with shrubs FMC practically the same as GVMI and NDII, and higher for NDWI. The former was no expected, since others studies with finer spatial resolution sensors such as Landsat-TM (Chuvieco et al., 2002) have reported lower correlations for NDVI than for NIR/SWIR indices. Therefore, our results might be due to LAI or border effects present in the coarse spatial resolution of MODIS. Lower than expected correlations for NDWI as computed from MODIS/Terra band 5, should be caused by the radiometric problems of this sensor that have been reported by several authors (Stow et al., 2005).

According to the previous analysis, regression models based on empirical data selected different variables to those based on simulated data. The former fittings tended to select indices based on the red/NIR space, such as NDVI or VARI, while the latter chose indices in the NIR/SWIR space, such as

Table 4 – Multiple regression results for FMC estimations based on empirical data (calibration set)

Sample	Grassland					Shrubland					
	r^2	a	b_1 (NDVI)	S.E.	n	r^2	a	b_1 (VARI)	b_2 (GVMI)	S.E.	n
0	0.907	−161.112	650.226	30.1	40	0.732	229.14	887.155	−300.751	17.5	40
1	0.870	−131.144	564.230	40.2	35	0.734	191.474	719.134	−216.348	13.3	42
2	0.879	−134.729	552.872	31.4	41	0.757	199.962	796.292	−222.873	15.9	35
3	0.845	−137.591	566.349	36.3	39	0.671	200.868	768.924	−234.900	18.1	41

Table 5 – Multiple regression results for FMC estimations based on RTM simulated data (calibration set)

Sample	Grassland						Shrubland					
	r^2	a	b_1 (LAI)	b_2 (NDII)	n	S.E.	r^2	a	b_1 DM	b_2 (GVMI)	S.E.	n
0	0.894	−6.74	131.41	296.751	1331	29.5	0.842	200.27	−5322.81	92.28	12.6	503
1	0.898	3.013	121.82	324.708	817	29.2	0.852	205.23	−5471.86	90.19	12.4	304
2	0.904	−7.746	132.31	287.376	792	29	0.844	203.161	−5472.86	96.46	12.7	298
3	0.897	−4.587	129.08	309.865	782	29.1	0.823	198.828	−5279.85	92.28	12.9	293

Table 6 – Results of the validation of the models (validation set)

	Empirical data					Simulated data				
	r^2	Slope	RMSE (%)	RMSEs (%)	RMSEu (%)	r^2	Slope	RMSE (%)	RMSEs (%)	RMSEu (%)
Grassland	0.9140	0.93	28.39	10.24	25.39	0.9268	0.92	24.57	8.69	22.99
Shrubland	0.7226	0.91	16.01	3.23	15.68	0.7034	0.56	25.18	19.17	10.10

the NDII or GVMI for grasslands or shrublands, respectively. The reason for that should be related to the indirect effects of water content variations on plant physiological activity. VARI or NDVI do not include bands with water absorption features, but they were selected in the empirical models because they are very sensitive to chlorophyll and LAI variations, which follow leaf drying in many species, and particularly in grasslands (Nelson, 2001). These indirect effects are not so evident for shrublands (Nuñez Olivera, 1988), and therefore the empirical models selected also indices including SWIR bands, such as the GVMI. This index was also selected by the simulation model, since it is well adapted to water absorption features. In fact, it was initially designed as a water content index (Ceccato et al., 2002), although it was intended for estimation of EWT (water per leaf area), and not for FMC (water per dry mass). However, with empirical data, the most explicative index was the VARI, which is a combination of blue, green and red reflectance, as it is proposed to estimate chlorophyll content of the upper canopy. The importance of VARI for FMC was also observed by other authors working in Mediterranean shrubs (Roberts et al., 2006; Stow et al., 2005).

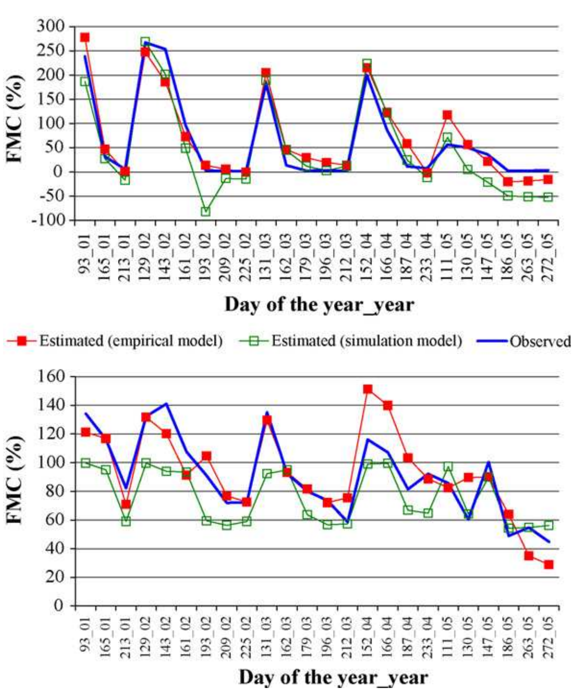

Fig. 6 – Temporal trends of FMC observed and estimated by both empirical and simulation models for grasslands (top) and shrublands (bottom).

NDII and GVMI, NIR/SWIR indexes, are selected in models based on simulation data. Red/NIR indices were not chosen because the indirect effects of water content on chlorophyll variations were not considered in the simulations, since the chlorophyll content was fixed. Chlorophyll content decrease with water deficit in *C. ladanifer* L., following an annual cycle with higher values in winter, lower in summer and intermediate in spring and autumn (Nuñez-Olivera et al., 1996; Gratani and Varone, 2004). The reason behind selecting a fixed chlorophyll value in the simulation was, that spring chlorophyll content can be attenuated under severe drought periods what can lead to slighter differences between spring and summer values (Valladares, personal communication). Years 2004 and 2005 were specially dry in our study site (Garcia, 2007), therefore average chlorophyll values for spring and summer were not significantly different (ANOVA, $p > 0.05$). Late spring is the period of maximum leaf shedding in *C. ladanifer* L., and hence mature leaves sampled during those days showed the relatively low chlorophyll content typical of senescent leaves (Nuñez-Olivera et al., 1996). Regarding grasslands, Billore and Mall (1976) found a clear bell-shape curve in chlorophyll content, with the peak just after the rain season, so more variations in chlorophyll content are likely to be found between spring and summer. Future work should be done to consider these variations in the grassland simulations and see if the models derived changes the tendency to choose indices including SWIR bands towards Red/NIR.

LAI variations were included in the grassland model, which is indirectly related to variations of red/NIR reflectance.

LAI and DM as external variables were introduced in the simulation data model based on the rules used to avoid unrealistic combinations and previous experience with RTM inversion software (Rueda, 2001), which only offered good results when LAI and DM were fixed. In this way the final simulated derived models account for variation in these two parameters.

Table 7 – Summary of advantages and disadvantages of empirical and simulated data in FMC estimation

	Simulated data	Empirical data
Calibration difficulty	High (requires detailed parameterization)	Low
Time to generate the model	High	Medium
Cost	Medium (reduces field sampling, but increases input variables that should be measured to parametrize the model)	High (intense field sampling)
Indices selected	NIR–SWIR space	Red–NIR space
Auxiliary data	High (Sun-Illumination Angles, LAI, DM, etc.)	Low (reflectance)
Robustness	High	Medium
Accuracy	Largely depend on range of input conditions and model assumptions	Largely depends on time series and spatial representativity of the sample

Both modeling approaches provided good estimations of grasslands and shrublands FMC, but those based on simulated data offered a lower standard error. Negative estimations of the grassland models were not considered a serious problem, since they occurred with actual FMC values below 30%, where these fuels can be considered as dead fuels (Nelson, 2001). In integrated systems of fire risk indices, the dead FMC estimation is carried out by means of meteorological indices, therefore, a filter could avoid these negative estimations to address this error. Therefore, the model based on simulated data should be considerable more suitable because it has a tendency to under-estimate FMC whereas the empirical model over-estimate FMC in the driest periods. From the fire prevention point of view, over-estimation is considered less desirable since it would tend to reduce the fire risk rating, although false alarms are also undesirable.

Some problems with the model derived from simulated data, especially those related to shrublands estimation, might be improved with the use of a wider range of parameters, or other inversion strategies, that will be considered in the near future. Additionally, new RTM better adapted to forested areas, such as geometrical or mixed geometrical-turbid medium models, such as GORT, DART, GEOSAIL (Pinty et al., 2004), may provide better inversion in shrublands as well as extending our efforts to tree-covered areas. The generalizing power of these simulation models remains to be proven, by extending the validation sample to other study areas, which we will also plan to perform in the near future.

5. Conclusions

Developing an operational methodology of FMC estimation is a key factor for fire risk assessment. Remote sensing offers operational tools to monitor this FMC evolution. The first results that compare the effectiveness of FMC estimations from empirical methods and those based on simulated data for two representative vegetation types (Mediterranean grassland and shrublands) were covered in this paper. The model based on empirical data offered reasonable results and it was easy to compute. The model based on simulation data, was more complex to generate, but proved more robust when several calibration samples were selected.

Further studies should test whether these models are applicable in other sites with similar environmental characteristics.

Acknowledgements

This research has been funded by the Firemap project (CGL2004-060490C04-01/CLI) and the Spanish Ministry of Education and Science by means of the FPU grant program which supports Marta Yebra. We would like to give special thanks to the authorities of the Cabañeros National Park and a large list of colleagues involved in the fieldwork. Suggestions and comments from Seth Peterson of UC Santa Barbara, Mark Danson of the University of Salford, Fernando Valladares (Centro de Ciencias Medioambientales, C.S.I.C.) and two anonymous reviewers are also acknowledged.

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