Remote Sensing of Environment 132 (2013) 59–70

Contents lists available at SciVerse ScienceDirect

Remote Sensing of Environment

journal homepage: www.elsevier.com/locate/rse

Regional estimation of woodland moisture content by inverting Radiative Transfer Models

Sara Jurdao [a,*], Marta Yebra [a,b], Juan Pablo Guerschman [b], Emilio Chuvieco [a]

[a] Department of Geography and Geology, University of Alcalá, Calle Colegios 2, 28801, Alcalá de Henares, Spain
[b] CSIRO Land and Water, GPO Box 1666, Canberra ACT 2601, Australia

ARTICLE INFO

Article history:
Received 20 July 2012
Received in revised form 3 January 2013
Accepted 5 January 2013
Available online 10 February 2013

Keywords:
MODIS
Look Up Table
Water-limited
Energy-limited
Mediterranean
Live Fuel Moisture Content
Fire risk
Fire danger

ABSTRACT

We inverted the PROSPECT and GEOSAIL Radiative Transfer Models (RTM) using Moderate Resolution Imaging Spectrometer (MODIS) data to retrieve Live Fuel Moisture Content (LFMC) in woodlands located in the peninsular territory of Spain. Ecological rules were used to parameterize the RTM. This approach reduces the probability of an ill-posed problem in the inversion of the selected RTMs, by rejecting unrealistic combinations of input parameters. Three species representatives of each region were used to derive the ecological rules: *Quercus ilex* L., *Quercus faginea* L., and *Pinus halepensis* Mill. for the Mediterranean region, and *Fagus sylvatica* L., *Quercus robur* L. and *Eucalyptus globulus* Labill for the Eurosiberian region. Equivalent Water Thickness, Dry Matter and Chlorophyll content were taken from several data sources to separately parameterize both the Mediterranean (water-limited) and Eurosiberian (energy-limited) ecoregions of Spain. GEOSAIL was parameterized using a restricted range of Leaf Area Index (LAI) and specific canopy cover values, keeping other parameters fixed. The inversion was based on the Look Up Table technique using the minimum spectral angle as merit function. Several models were tested by using different inputs from standard MODIS products, as well as the fractional cover product developed by Guerschman et al. (2009). The model based on the reflectance bands and the Normalized Difference Infrared Index computed from the Nadir Bidirectional Reflectance Distribution Function-Adjusted Reflectance product (MCD43A4) provided the most accurate results, with a LFMC's Root Mean Square Error (RMSE) of 27.7% (RMSE = 27.3% for the Mediterranean and 28.7% for the Eurosiberian woodland). The estimation of LFMC was performed within the framework of a fire risk assessment system.

1. Introduction

Wildland fires have a wide range of global and regional impacts. Fire is a natural agent of many ecosystems, which are well adapted to periodical burning or even dependent on it, as fire impacts nutrient cycles, vegetation succession patterns, and resistance to insect plagues (Kilgore, 1973). However, fires have also negative impacts on soil erosion (Boerner et al., 2009), on emissions of atmospheric aerosols and greenhouse gases (van der Werf et al., 2006), on the extent of deforestation (van der Werf et al., 2009), while they can be harmful to human health and welfare (Sandberg et al., 2002). During the last decades, the repeated occurrence of severe wildfires affecting various parts of the world and the consequent increment of their negative impacts has highlighted the need to develop effective tools to assess and eventually mitigate these phenomena (Ceccato, 2001; Chuvieco et al., 2010). Since fire regimes (frequency, size, seasonality and severity of fires) are a function of weather conditions and terrain features, as well as the structure and moisture content of the fuel (Conard and Solomon, 2008; Ward et al., 1996), estimating the latter is critical for assessing fire risk.

Most fires burn during low Fuel Moisture Content (FMC) conditions (Chuvieco et al., 2009a; Dennison et al., 2008) as FMC is highly related to fire ignition and propagation (Viegas et al., 1992; Zylstra, 2011). FMC is frequently defined as the amount of water per dry mass of the fuel and formulated as follows:

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

where W_w is the wet weight and W_d is the dry weight obtained after oven drying the same sample at 60 °C–100 °C for 24–48 h (Viegas et al., 1992).

FMC can be estimated from ground measurements, weather indices and satellite imagery. The former are simple, but time consuming, costly, difficult to generalize, and may be subject to large sampling errors when a standard protocol is not followed (Danson and Bowyer, 2004). However, they are useful for calibration or validation purposes (Chuvieco et al., 2004b). FMC estimation based on meteorological indices has been commonly used by forest services, particularly to estimate moisture conditions of dead fuels (de Groot et al., 2005; Pellizaro et al., 2007). For live

* Corresponding author. Tel.: +34 91 885 5257; fax: +34 91 885 4439.
E-mail addresses: sara.jurdao@uah.es (S. Jurdao), marta.yebra@csiro.au (M. Yebra), juan.guerschman@csiro.au (J.P. Guerschman), emilio.chuvieco@uah.es (E. Chuvieco).

0034-4257/$ – see front matter
http://dx.doi.org/10.1016/j.rse.2013.01.004

fuels, weather indices perform poorer, as they do not take into account the physiological mechanisms of plants to resist drought. Satellite data is the only feasible means of spatially estimating Live FMC (LFMC), assuming that variations in moisture content have a strong impact on reflectance (Bowyer and Danson, 2004) and/or surface temperature trends (Chuvieco et al., 2004b).

Estimations of LFMC from satellite data have been most commonly based on empirical methods, which aim to find statistical relations between field-measured LFMC and reflectance data. Several studies have shown strong agreements between LFMC and information provided by different sensors, such as NOAA/AVHRR (Burgan et al., 1996; Chuvieco et al., 2004a, 2004b; Garcia et al., 2008), Landsat-TM/ETM (Chuvieco et al., 2002), VEGETATION (Chuvieco et al., 2004b), AVIRIS (Roberts et al., 2006), and MODIS images (Dennison et al., 2005; Yebra et al., 2008b). However, empirical models require a long time series of field measured LFMC to calibrate the models (Chuvieco et al., 2009b). Furthermore, empirical relationships are site and sensor dependent, and therefore difficult to extrapolate to regional or global scale studies (Riaño et al., 2005b; Yebra et al., 2008a).

Simulation studies based on Radiative Transfer Models (RTM) have been used more recently to overcome these limitations (Ceccato et al., 2002; Yebra and Chuvieco, 2009b; Yebra et al., 2008b; Zarco-Tejada et al., 2003). LFMC is not a parameter used in any of the existing simulation models, but can be obtained by the ratio between two of the input parameters commonly found in RTM (2).

$$\mathrm{LFMC} = \frac{\mathrm{EWT}}{\mathrm{DMC}} \tag{2}$$

where EWT is the Equivalent Water Thickness (3) and DMC is the Dry Matter Content (4).

$$\mathrm{EWT} = \frac{W_w - W_d}{\mathrm{leafArea}} \tag{3}$$

$$\mathrm{DMC} = \frac{W_d}{\mathrm{leafArea}}. \tag{4}$$

Despite the high potential of RTM to retrieve LFMC, their accuracy is affected by non-singular inversions, as similar spectra may be generated from different combinations of input parameters. This is called the “ill-posed” problem (Combal et al., 2002), which may dramatically decrease the accuracy of LFMC estimates (Yebra and Chuvieco, 2009b). Previous studies have proved that including ecological criteria in the parameterization of the RTM can consistently improve the estimates of LFMC, since it avoids simulating unrealistic spectra which might produce indetermination problems when inverting the model (Yebra and Chuvieco, 2008; 2009a, 2009b). There are mainly three different ways of introducing the ecological information of biophysical parameters: (i) restricting the range of parameter variation, (ii) using empirical relationships to filter out the unrealistic combinations of parameters within that range, and (iii) using a complete set of realistic measurements. Ecologically driven parameters may be obtained from two different sources: (i) experimental data (either field conditions or controlled laboratory experiments) and (ii) remotely measured data provided by airborne or satellite sensors.

This paper proposed an innovative method to retrieve LFMC values of woodlands using optical remote sensing and RTM. The final aim of this project was to incorporate the estimation of LFMC values into a fire danger assessment system (Chuvieco et al., 2012). Five inversion scenarios have been tested, based on different combinations of input bands and external parameters, as well as on comparing the performance of standard MOD09 and MCD43 products to retrieve LFMC. In all cases, the parameterization of RTM is based on ecological criteria to reduce indetermination problems in the inversion process. This approach builds upon our previous experience on estimating LFMC of grasslands and shrublands (Yebra and Chuvieco, 2009b; Yebra et al., 2008b), by extending the simulation to woodlands of two different climatic regions of Spain.

2. Data and methods

2.1. Study areas and species selection

Two climate regions determine the biogeography of Spain: (i) the Eurosiberian (northern Spain), and (ii) the Mediterranean (Rivas Martínez, 1983, Fig. 1). The Mediterranean region is a water-limited biome which covers 4/5 of the Iberian Peninsular territory of Spain (~390,000 km^2). It presents dry summers, high thermal amplitude, and low precipitation (between 400 and 500 mm). Therefore, the woody vegetation in this region is mainly evergreen sclerophyll with hard and small leaves well adapted to drought. In contrast, the Eurosiberian region is an energy-limited environment which covers the remaining 1/5 of the Iberian Peninsular territory of Spain (~100,000 km^2). It presents abundant rainfall (up to 2000 mm) even in the summer season, and its landscape is characterized by its greenness and the dominance of deciduous species.

In light of these climatic and ecological differences between the two regions, we decided to consider different ecological criteria in the parameterization of the RTM for each region. Three representative species of the common land cover types of each biogeographical region were selected. *Quercus ilex* L., *Quercus faginea* L. and *Pinus halepensis* Mill. were the species selected as representatives of the evergreen broadleaf (EBF), deciduous broadleaf (DBF) and evergreen needleaf forest (ENF), respectively in the Mediterranean-water-limited environment while *Fagus sylvatica* L., *Quercus robur* L. (both DBF) and *Eucalyptus globulus* Labill. (EBF) were selected as representatives of the main land cover types in the Eurosiberian-energy-limited environment (Fig. 1).

These species were selected because the Spanish landscape is a continuous mosaic of coexisting physiologically distinct plants which have evolved different drought strategies so it would have been not feasible to consider ecological criteria of all species concurring in each region.

2.2. Radiative transfer modeling

2.2.1. Model selection

Previous studies have estimated moisture of woodlands linking the leaf-level PROSPECT RTM to the canopy-level SAILH RTM (Colombo et al., 2008; Trombetti et al., 2008; Yebra and Chuvieco, 2009a). PROSPECT (Jacquemoud, 1990) simulates leaf reflectance and transmittance by describing the leaf as a set of N homogeneous layers with some scattering and absorption components: Chlorophyll content (C_{a+b}, μg/cm^2), EWT (g/cm^2), and DMC (g/cm^2). SAILH (Verhoef, 1984) is a 1D turbid medium plane-parallel simulation model specifically designed for continuous cover structure such as grassland. However, Trombetti et al. (2008) pointed out that part of the inaccuracies in the estimations in woodlands can be explained by the fact that SAILH was specifically designed for continuous cover structure, such as grasslands, and not for discontinuous and heterogeneous vegetation types. Therefore, a canopy level RTM specifically designed for discontinuous canopies may lead to more accurate estimations. In this study we linked PROSPECT to GEOSAIL (Huemmrich, 2001). GEOSAIL combines a geometric model that calculates the amount of shadowed and illuminated components in the scene (sunlit canopy, shaded canopy, sunlit background, and shaded background) with the SAILH turbid medium RTM. Hence, GEOSAIL shares with SAILH the following inputs: leaf reflectance and transmittance (in this case taken from PROSPECT outputs); two parameters describing the canopy structure (LAI and Leaf Inclination Distribution Function (LIDF)), soil substrate reflectance and four parameters which characterize the viewing and illumination conditions (solar zenith angle or θ_s, viewing zenith angle or θ_v, relative azimuth angle or φ_{sr} and atmospheric transmissivity). However, GEOSAIL includes three new parameters: canopy cover of vegetation

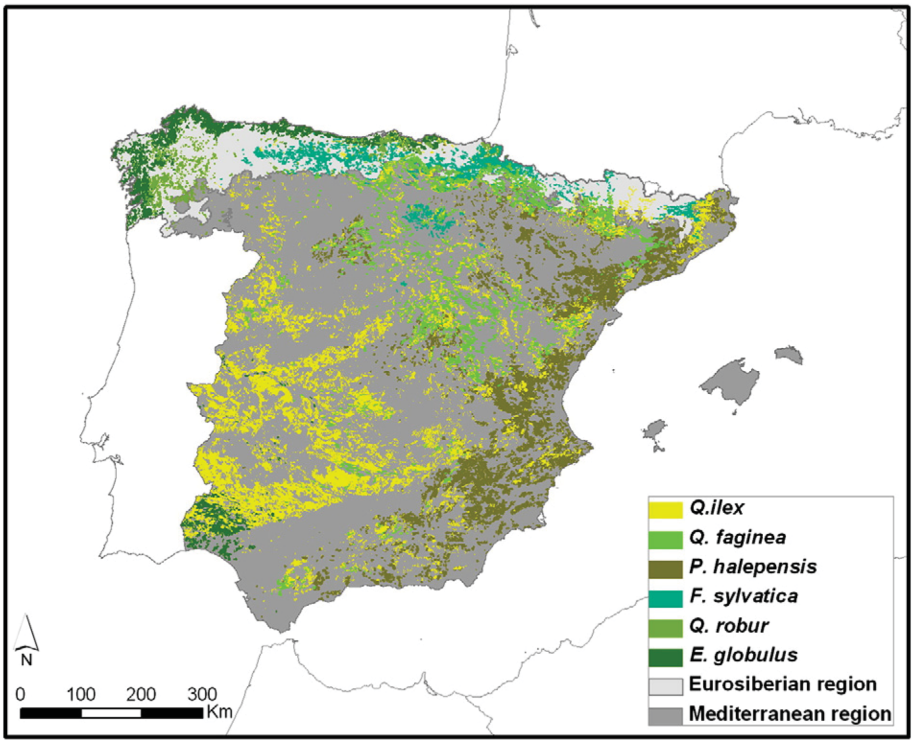

Fig. 1. Representativeness of the species selected for the RTM calibration. Information taken from the Spanish Forest Map, (1:200,000) (http://www.magrama.gob.es/es/biodiversidad/servicios/banco-datos-naturaleza/informacion-disponible/mfe200.aspx, last accessed September, 2012).

(ccov), the ratio Canopy of Height to Width (CHW) and crown shape (cylinders or cones). Finally, GEOSAIL assumes that trees are identical, they do not overlap and are relatively small in size compared to the size of the pixel (Huemmrich, 2001).

GEOSAIL has proven to provide satisfactory results in several forestry applications on coniferous canopies such as burn severity (De Santis et al., 2009) and structure and foliage water content assessment (Kötz et al., 2004) but, to our knowledge, has not been applied to date for estimating LFMC.

2.2.2. Model ecological parameterization

2.2.2.1. PROSPECT parameters. PROSPECT parameters were introduced as a complete set of observed co-occurring measurements taken for each representative species from several sources that included laboratory and field data (Table 1). For the sake of simplicity Table 1 shows the minimum, maximum and average values as an overview of the ranges of variation of each parameter among the observations.

Leaf-level information of *F. sylvatica*'s parameters was not found in the literature so a field campaign was organized to get information for this specie. The field campaign was carried out from the 24th of May to the 28th of September of 2010 in two plots (plots 1 and 2, Fig. 2) placed in the north of Spain.

DMC and EWT were computed from the collected samples as Eqs. (3) and (4). W_w was calculated weighing a fresh sample with a precision balance (±0.01 g) and W_d oven drying the same sample at 60 °C for 48 h. Leaf area was measured with an image analysis Delta system (Delta Devices LTD, Cambridge, England). The C_{a+b} values were obtained by means of destructive sampling and measurement in the laboratory with the dimethyl sulfoxide method and

Table 1
PROSPECT input parameters and sources. Shown are the Minimum (Min.); Maximum (Max.); Average (Avg.); Chlorophyll content (C_{a+b}), μg/cm^2; Equivalent Water Thickness (EWT), g/cm^2; Dry Mater Content (DMC), g/cm^2; Number of co-occurring measurements included in the forward modeling (# obs).

PROSPECT		C_{a+b}	EWT	DMC	# obs	Source	
Q. ilex	Min.	71.68	0.004	0.013	32	De Santis et al. (2006)	Laboratory data
	Max.	95.68	0.023	0.024			
	Avg.	82.95	0.014	0.018			
Q. faginea	Min.	35	0.009	0.011	14	Chuvieco et al. (2011)	Spain
	Max.	45	0.022	0.016			
	Avg.	41.92	0.012	0.013		Silla et al. (2010)	
P. halepensis	Min.	33.32	0.006	0.011	54	Jurdao et al. (2012)	Laboratory data
	Max.	66.15	0.054	0.046			
	Avg.	47.26	0.036	0.029		Gond et al. (1999)	Belgium
F. sylvatica	Min.	30	0.005	0.003	29	This study	Spain
	Max.	30	0.018	0.011			
	Avg.	30	0.010	0.007	14	Gond et al. (1999)	Belgium
Q. robur	Min.	9.21	0.009	0.004			
	Max.	49.18	0.016	0.011			
	Avg.	33.87	0.013	0.008			
E. globulus	Min.	45.47	0.008	0.013	19	Karen Barry, unpublished	Australia
	Max.	98.74	0.027	0.028			
	Avg.	75.68	0.022	0.022			

spectrophotometric readings, according to Wellburn (1994). C_{a+b} of *F. sylvatica* was fixed to 30 μg/cm^2 since simultaneous measurements with EWT and DMC were not performed. This representative value was obtained averaging the C_{a+b} of 32 samples of *F. sylvatica* leaves taken during the field campaign described above.

The PROSPECT parameter N is not measurable so indirect estimations using RTM inversion are normally used. This way, Gond et al. (1999) obtained minimum, maximum and average N values of 2.13, 3.44 and 2.48 for *P. sylvestris* and 1.22, 1.55 and 1.45 for *Q. robur*. The values obtained by the authors for *P. sylvestris* were assigned to our needle-leaved species since we assumed similar internal structures while the values for *Q. robur* were used only for this specie. For the rest of the species N was fixed to 2 as it is a common value found in literature for woodlands (Barry et al., 2009; De Santis et al., 2006; Yebra and Chuvieco, 2009a).

2.2.2.2. GEOSAIL parameters. GEOSAIL input parameters were also taken from diverse sources (Table 2). The range of LAI was restricted to minimum and maximum values obtained from different sources. The distribution within each range was generated based on a transformed variable (LAI_t) established by Weiss et al. (2000) (Eq. (5)). The aim was to better sample domains where the reflectance is more sensitive to LAI. This way lower values of LAI are more sampled.

$$LAI_t = (-2) * \log(LAI). \tag{5}$$

CHW was fixed to the average value measured in 30 individuals studied in the field (Table 2). It was calculated as the ratio between the crown height (total tree height subtracting the trunk height) and the crown width (taken the highest diameter).

LIDF was fixed as plagiophile for all species with the exception of *E. globulus* and *P. halepensis* for which it was fixed to erectophile and spherical, respectively. The crown shape was considered cylindrical for all species except for *P. halepensis* which was observed to better resemble a cone. A reference soil spectrum was measured using the GER2600 spectroradiometer in a national park located in the center of Spain and was used in both studied regions. This ground spectrum was multiplied by a dry brightness parameter (1.4) to simulate a reference dry soil in the Mediterranean region following Yebra and Chuvieco (2009b). The ccov was distributed from 0.4 to 1 and 0.6 to 1 for the Mediterranean and Eurosiberian forest respectively, since the former generally presents less canopy cover than the latter. In both cases, the step for the simulations was 0.2. Finally, all viewing angles were fixed to 0 assuming a vertical observation.

2.2.3. Forward modeling

Once the RTM were ecologically parameterized, PROSPECT and GEOSAIL were jointly run to obtain a total of 6336 and 1146 simulated spectra for the Mediterranean and the Eurosiberian region, respectively (Fig. 3). Some of the resulting spectra were considered unrealistic since they were simulated using random combinations of the leaf parameters with LAI (only restricted to a range of values). For instance, under drought conditions (i.e., with low LFMC values), plants tend to reduce the leaf area (Valladares, 2004) so the LAI is also reduced and high LAI values do not normally concur with LFMC below 30%. In order to avoid this spectra that were not likely to occur we used two empirical relationship between LFMC and LAI (one for each region) as a filter criterion to remove all spectra whose LFMC vs. LAI values were placed out of the range derived from the minimum and maximum residuals of the model equations (Yebra and Chuvieco, 2009b; Yebra et al., 2008b). The empirical relation for the Mediterranean region (Fig. 3) was fitted using LFMC field observations of *Q. ilex* vs. LAI derived from the MOD15A2v4 product (Myneni et al., 2000). The Mediterranean model was constrained to 3336 spectra after using this filtering criterion. In the Eurosiberian region the relationship between LFMC vs. LAI was weak ($R^2 = 0.18$) so we decided not to used this relation to filter the spectra for this region.

Finally, to allow the simulated spectra to resemble MODIS data, the spectra were convolved to the 7 MODIS reflectance bands.

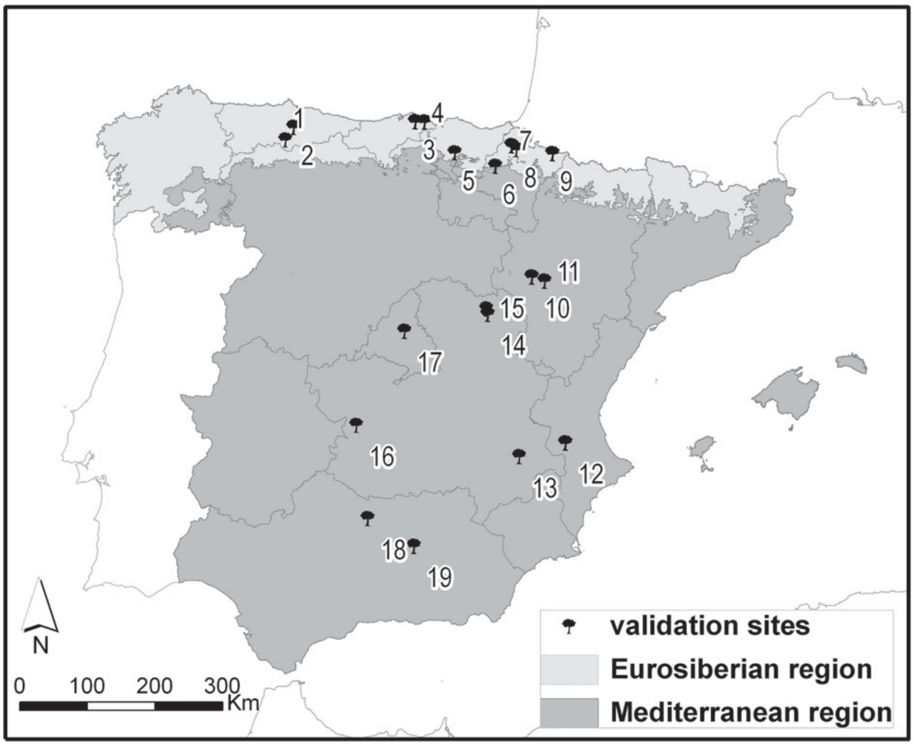

Fig. 2. Location of the validation sites among the Eurosiberian (energy-limited environment) and the Mediterranean (water-limited environment) region.

Table 2
GEOSAIL input parameters and sources. Shown are the minimum (min) and maximum (max) values of Leaf Area Index (LAI) and Canopy Height to Width (CHW).

GEOSAIL		LAI			CHW		
			Source			Source	
Q. ilex	Min.	0.6	De Santis et al. (2006)	Spain	1.89	Mariano García, unpublished	Spain
	Max.	2.1	Mariano García, unpublished		1.89		
Q. faginea	Min.	0.6	Chuvieco et al. (2011)	Spain	2.43	Chuvieco et al. (2011)	Spain
	Max.	2.1			2.43		
P. halepensis	Min.	0.9	Riaño et al. (2004)	Spain	3.35	Mariano García, unpublished	Spain
	Max.	2.1	López et al. (2000)		3.35		
F. sylvatica	Min.	2.4	Dufrêne and Bréda (1995)	France	1.8	Field data*	Spain
	Max.	6	Le Dantec et al. (2000)		1.8		
Q. robur	Min.	2.5	Gond et al. (1999)	Belgium	1.5	Field data*	Spain
	Max.	5	Hytteborn (1975)	Sweden	1.5		
E. globulus	Min.	3	Karen Barry, unpublished	Australia	1.62	Field data*	Australia
	Max.	4.5			1.62		

* Data from field work carried out by the authors for the present paper.

2.2.4. Model inversion: RTM backward mode

The inversion of RTM can be achieved following two main alternative approaches (Kimes et al., 2000; Weiss et al., 2000): (i) building statistical relationships developed over simulated reflectance and their corresponding LFMC by using linear regression (Yebra et al., 2008b) or neural networks (Riaño et al., 2005a); (ii) adjusting the set of values of the RTM inputs in such a way that the simulated spectrum matches the best reflectance measured by a sensor in a range of wavelengths using a merit function of spectra similarity. This adjustment can be made by iterative optimization techniques (Zarco-Tejada et al., 2003) or simulated look up tables (LUT) (Knyazikhin et al., 1999). In this study, the LUT inversion technique was chosen since it requires less computation time than other methodologies and allows the creation of realistic simulations by including ecological criteria (Combal et al., 2002; Liang, 2004; Yebra and Chuvieco, 2009b; Yebra et al., 2008b).

The spectral angle (SA, Eq. (6), Kruse et al., 1993) was used as the merit function. SA is insensitive to illumination or albedo effects and can be applied to a whole image (De Santis and Chuvieco, 2007). The parameters used to model the selected particular spectrum (w) were assigned to the target pixel and then LFMC was estimated as the ratio between EWT and DMC (Eq. (2)). The estimated LFMC was then compared to the observed LFMC (Section 2.3, validation).

$$SA\left(\vec{v},\vec{w}\right) = \cos^{-1}\left(\frac{\vec{v}\times\vec{w}}{\|\vec{v}\|\times\|\vec{w}\|}\right) \quad (6)$$

where v and w are the observed (satellite image) and the reference (LUT) spectra respectively, both of them considered as an m-dimensional feature vector, with m being the number of spectral channels.

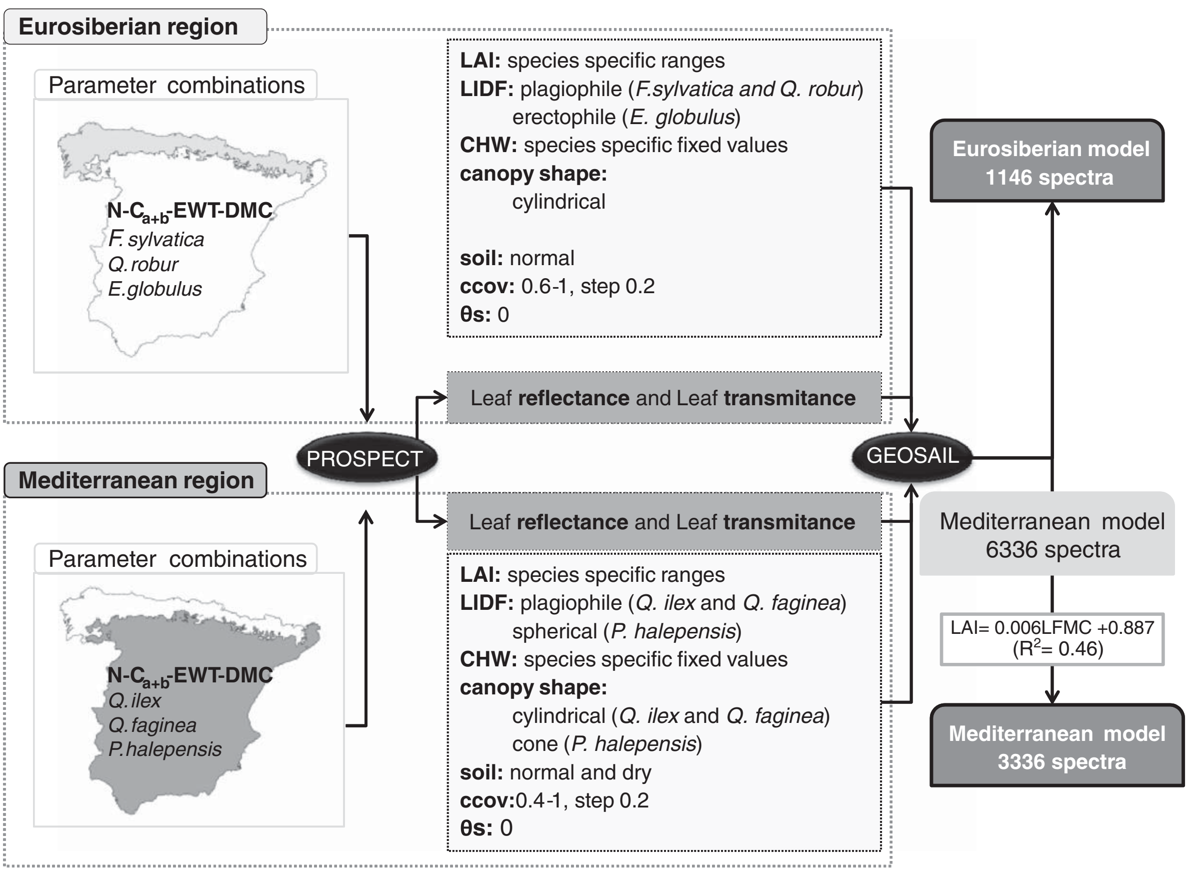

Fig. 3. Workflow followed to create the set of simulations.

Yebra and Chuvieco (2009a) explored several inversion options obtaining the most accurate LFMC estimates when the MODIS reflectance bands were considered in the inversion (RMSE≈30%), or when it was performed just using the "Normalized Difference Infrared Index" ($NDII_6$, Eq. (7)), (Hardisky et al., 1983), (RMSE=26.28%)

$$NDII_6 = \frac{\rho_{band2} - \rho_{band6}}{\rho_{band2} + \rho_{band6}}. \quad (7)$$

Following these findings, we decided to include in the inversion, the seven reflectance bands from MODIS and also the $NDII_6$.

Two alternative sources of reflectance data from MODIS were tested: 500 meter surface reflectance data product (MOD09A1) and the 500-meter Nadir BRDF-Adjusted reflectance product (MCD43A4) (Table 3, approaches 1 and 2 respectively). Previous LFMC studies have mainly used the MOD09A1 reflectance product (Peterson et al., 2008; Yebra and Chuvieco, 2009b; Yebra et al., 2008b). This product (Vermote and Vermeulen, 1999) is an 8-day composite of atmospherically corrected reflectance for the first seven spectral bands of the MODIS Terra sensor. However, we also explored MCD43A4 as it provides land surface reflectances as if they were taken from the nadir which is more consistent with our simulations. Additionally, the corrections of this product significantly reduces noise due to anisotropic scattering effects of surfaces under different illumination and observation conditions (Schaaf et al., 2002), and being a 16-day composite (also computed every 8-days as the MOD09A1) which contains data from both Terra and Aqua MODIS sensors, it provides the highest probability for quality input data. For both reasons, we expected to achieve better results with MCD43A4 than MOD09A1 MODIS product.

Finally following several authors who obtained improvements in water content estimation when some of the input parameters were fixed to a known value in the inversion, we tested three additional inversion approaches using the best performing MODIS reflectance input (previously assessed), and fixing different RTM parameters with the help of ancillary remote sensing information. Approach 3 fixed LAI obtained from the MOD15A2 product (Myneni et al., 2000). This product is an 8-day composite of LAI and fractional photosynthetically active radiation at 1 km spatial resolution. According to previous studies that fixed LAI in the inversion (Yebra et al., 2008b; Zarco-Tejada et al., 2003),this approach lead to better results since LFMC and LAI compensated creating indetermination problems when high LFMC with low LAI are observed in the field, but low LFMC with high LAI are simulated, and vice versa. Those two alternative combinations of LFMC and LAI yield similar spectra.

Approaches 4 and 5 fixed canopy coverage (ccov parameter in GEOSAIL) using two different data sources (Table 3): (i) the vegetation continuous field product (MOD44B, Hansen et al., 2001) and (ii) the fractional cover product developed by Guerschman et al. (2009). The former contains percent estimates of tree cover using a supervised regression tree algorithm at 500 m spatial resolution (Hansen et al., 2003). The latter separates the fractions of photosynthetic vegetation, non-photosynthetic vegetation and bare soil by a linear unmixing procedure using the normalized difference vegetation index and the ratio of MODIS bands 7 and 6 (Guerschman et al., 2009). The fractional cover of the non-photosynthetic vegetation and the photosynthetic vegetation were summarized to get the canopy cover.

Table 3
Inversion approaches checked. Crosses mark the MODIS bands, indexes or canopy parameters used for the computation of the similarity function.

Inversion approach	B1–B7	$NDII_6$	LAI	Ccov	Source
1	X	X			MOD09A1
2	X	X			MCD43A4
3	X	X	X		MCD43A4.MOD15A2
4	X	X	X	X	MCD43A4.MOD44B
5	X	X	X	X	MCD43A4.Guerschman et al. (2009)

All MODIS data (MOD09A1, MCD43A4, MOD15A2 and MOD44B) were downloaded from (http://reverb.echo.nasa.gov/reverb/, last accessed February, 2012) and reprojected from the sinusoidal system to the UTM coordinate system (Datum European 1950), using nearest neighbor interpolation resampling. Additionally, MOD15A2 imagery was oversampled to a spatial resolution of 500 m. Then, the data were extracted selecting homogeneous pixels from the vicinity of the plots inside a 3×3 window avoiding mixed pixels, in order to reduce the potential noise derived from georeferencing errors. For this, higher spatial resolution images from Landsat (http://glovis.usgs.gov/, last accessed May, 2012) were used. Following Yebra et al. (2008b), the final estimate LFMC value for each validation site was computed as the median value of the pixels assigned to each plot.

2.3. Validation

A total of 154 field measurements of LFMC were taken from the database compiled by our research group at the University of Alcalá (http://www.geogra.uah.es/emilio/FMC_UAH.html, last accessed May, 2012) (Table 4). This database includes data collected by several field campaigns carried out in the framework of different projects and with contributions from other organizations. The sampling areas were distributed among 19 plots within the Iberian Peninsula (Fig. 2) and constitute homogeneous patches of 500×500 m to be representative of a MODIS pixel. Most of the sites were located in the Mediterranean region of the country, which also has a longer time series (some of the plots from 1996 to 2010). Sites in the Eurosiberian region were sampled for the present study and only two years of data were available (2009 and 2010).

Three samples per plot were collected between 12 and 16 h GMT (at the time of maximum fire danger, Castro et al., 2006). Each sample was composed of between 80 and 100 g of leaves randomly selected from different trees. The sample was taken from the lower as well as the upper parts of the crown, whenever they were reachable with a 4 m long pole with scissors. The sample was weighed in the field with a field balance (precision ±0.01 g). All samples were then carried to the laboratory where they were dried in an oven for 48 h at 60 °C (Viegas et al., 1992). Afterwards, the samples were weighed again on the same balance to obtain the dry weight. LFMC was computed following Eq. (1). Average values of the three samples per plot were assigned to each plot for each sampling date. The standard sampling protocol is described in more detail in Chuvieco et al. (2011).

The accuracy of the models was assessed with data pooled across sites using the determination coefficient (R^2), the slope of the relationship between estimated and observed LFMC values and the Root Mean Square Error (RMSE) (Eq. (8)). The RMSE was decomposed into systematic (RMSEs) and unsystematic (RMSEu) portions (Willmott, 1982) in order to provide a quantitative measurement of the error caused by the model performance and its predictors (RMSEs) and the error caused by uncontrolled factors (RMSEu). An adequate model is considered to have an RMSEu higher than the RMSEs as the model estimates errors should be random.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}\left(LFMC_{i,obs} - LFMC_{i,est}\right)^2}{n}} \quad (8)$$

where $LFMC_{i,obs}$ and $LFMC_{i,est}$ are the observed and the estimated LFMC respectively, and n is the number of observations. RMSE are expressed in percentage of fuel dry weight, the same unit as the LFMC.

Finally, the best performing approach was tested for each region in order to take into account their influence on the final errors. The ideal model would accurately predict LFMC for any site.

Table 4
Description of the validation sites. #obs: number of observations; $LFMC_{min, max}$: minimum and maximum LFMC. For plots with one observation the only LFMC measurement is shown.

Eurosiberian region				Mediterranean region			
Id	Dominant species	#obs	$LFMC_{min, max}$ (%)	Id	Dominant species	#obs	$LFMC_{min, max}$ (%)
1	*Fagus sylvatica*	10	105.47, 173.62	10	*Pinus pinaster*	16	58.90, 125.46
2	*Castanea sativa*	15	126.58, 173.04	11	*Quercus ilex*	20	49.51, 132.26
3	*Eucaliptus globulus*	2	92.30, 103.73	12	*Pinus pinaster*	1	118.89
4	*Quercus ilex*	2	73.14, 103.71	13	*Pinus halepensis*	1	87.42
5	*Quercus pirenaica*	11	107.42, 178.62	14	*Pinus nigra*	3	104.96, 111.23
6	*Fagus sylvatica*	2	93.67, 214.81	15	*Quercus ilex*	3	112.77, 160.52
7	*Fagus sylvatica*	2	150.78, 251.63	16	*Quercus faginea*	54	72.95, 151.23
8	*Quercus robur*	1	128.04	17	*Quercus ilex*	6	15.65, 53.80
9	*Fagus sylvatica*	1	129.31	18	*Olea europea*	2	88.67, 116.83
				19	*Quercus ilex*	2	90.94, 110.23
Total		46		Total		108	

3. Results

3.1. Ecological simulation scenarios

In both regions under study, the observed and parameterized LFMC values presented similar ranges (Table 5), which implies that the input parameters for the RTM were realistic. Although the lowest observed LFMC values (15.6%) are not commonly found in Mediterranean woodland, they may occur in exceptionally dry summers (De Santis et al., 2006). This was considered in the parameterization of the RTM in the Mediterranean region, which presented a minimum parameterized LFMC value of 20.8%. The woodlands in the Eurosiberian region have higher LFMC values, as this climate is more humid. This was reflected by higher minimum and maximum parameterized values than in the Mediterranean region.

The resulting spectra obtained by the ecological simulation scenarios showed the expected effects in reflectance produced by different LFMC conditions (Fig. 4). On one hand reflectance on bands 3, 4 and 1 increase as LFMC decreases due to the impacts in chlorophyll content and LAI (Hardy and Burgan, 1999). On the other hand, reflectance in bands 5, 6 and 7 increases since these bands are the most sensitive bands to water absorption in the solar spectrum (Danson et al., 1992).

3.2. Validation

Fig. 5 shows total, systematic and unsystematic errors (RMSE, RMSEs and RMSEu, respectively) for the whole study area and the different inversion approaches tested in this paper. In terms of error distribution, the best performing models are those with the lowest RMSE, with similar values of RMSE and RMSEu, and with RMSEs close to 0. Following these criteria, the best inversion method was approach 2, based on the 500-meter MCD43A4 product. This inversion yielded an RMSE<30%, similar to RMSEu and 10% of RMSEs. Approach 1 (based on the MOD09A1 product) presented higher errors (RMSE = 49.8%). Although the slope of the regression between observed and estimated LFMC was closer to 1 (Fig. 6a) than approach 2 (Fig. 6b), the later presented higher R^2 (=0.5). Approach 3 (using MOD15A1 to fix LAI in the inversion) did not improve the results, as R^2 decreased to 0.3, the slope of the observed-estimated regression decreased to 0.71 (Fig. 7a), and the RMSE increased to values >35% (Fig. 5). The worst results were obtained from approach 4 (fixing canopy cover using MOD44B estimates), which resulted in close to 60% RMSE (Fig. 5). The slope was close to 1 but the R^2 decreased while increasing the errors (R^2 = 0.3, Fig. 7b). Finally, approach 5, fixing ccov using the product of Guerschman et al. (2009), provided better results than approach 4 (R^2 = 0.5 and RMSE ≈ RMSEu ≈ 30% and RMSEs < 10%, Figs. 7c and 5) with the exception of the slope that was lower, though still close to 1 (slope = 0.88).

Fig. 8 shows the same models split into the two ecoregions. The inversion of the ecological oriented RMT with MCD43A4 (approach 2) performed practically the same in both regions without a clear bias towards one of them (RMSE ≈ 30%). Additionally, as we observed when pooling the data across sites, the errors caused by the model performance and the predictors included (RMSEs) were nearly half the errors produced by uncontrolled factors (RMSEu) in both regions, although RMSEs was slightly lower for the Eurosiberian region. Approach 1 showed better results than when considering both regions together (RMSE < 40% in both regions). With approach 3, the results worsen especially in the Eurosiberian region where the RMSEs smoothly decreases but the RMSE significantly increased to values >50% (Fig. 8). In the case of approach 4, the decrease in the accuracy affected both regions but again the Eurosiberian region was stronger affected (RMSE > 50% and > 70%, for the Mediterranean and Eurosiberian region, respectively). The ccov product used with approach 5 demonstrated its usefulness in both regions considered (RMSE ≈ 30%, Fig. 8) although it did not significantly improve the results in relation to the approach 2 in which only the MCD43 was employed in the inversion.

Table 5
Statistics of the observed LFMC (Obs.) and parameterized LFMC (Param.) per Region; Min., minimum; Max., maximum. All results are shown in % of LFMC.

	$LFMC_{Min}$		$LFMC_{Max}$	
	Obs.	Param.	Obs.	Param.
Mediterranean region	15.6	20.8	160.5	169.2
Eurosiberian region	73.1	63.5	251.6	310

4. Discussion

Our results showed that LFMC values can be estimated with an uncertainty of 30%. Considering that tree species have most commonly LFMC values of 70 to 180%, this level of uncertainty is quite relevant in terms of fire risk assessment, particularly for the Summer season,

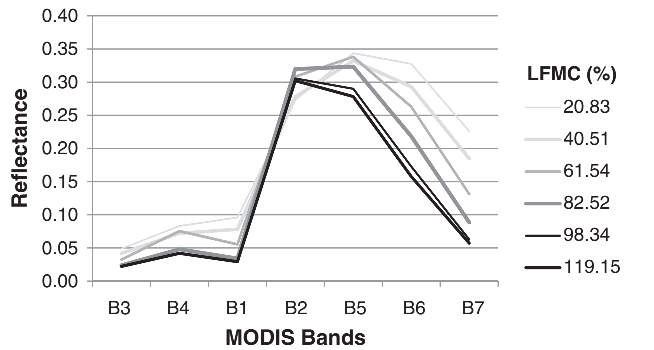

Fig. 4. Simulated MODIS reflectances randomly selected from the LUT and their corresponding LFMC parameterized values.

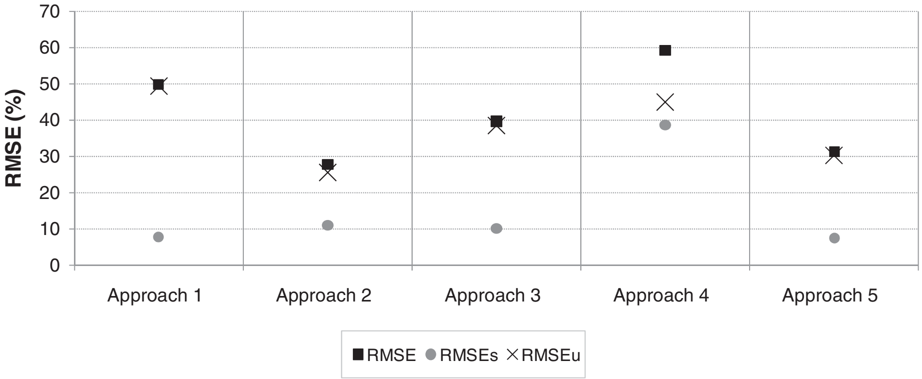

Fig. 5. Evaluation of the inversion of PROSPECT + GEOSAIL to estimate LFMC against observed LFMC across sites. The inversion was based on the reflectance bands and the $NDII_6$ using different input datasets (see Table 3).

although our study found the highest errors at the Spring time (RMSE = 31.13 and 25.72% for the Mediterranean region in the Spring and in the Summer season respectively, and RMSE = 34.88 and 26.58% for the Eurosiberian region in the Spring and in the Summer season respectively). Therefore, additional efforts need to be put in this challenging research area, taking into account the fact that there are many sources of uncertainty, such as the diversity of species coexisting in a pixel, the standard deviations between ground samples, the degree of mixtures within a MODIS pixel, etc. A similar level of errors were found by Yebra and Chuvieco (2009a) in an oak forests (RMSE = 26.28%), but in this case the authors targeted a single species (*Q. ilex*) which is very common in Mediterranean areas. Our study is more promising in this regard, as similar accuracy was obtained for a much wider species range, including not only the Mediterranean, but the Eurosiberian region as well.

The determination coefficient derived from our best model which make used of MCD43 reflectance data ($R^2 = 0.5$, Fig. 6b), was similar to the values obtained by Trombetti et al. (2008) ($R^2 = 0.6$) in the estimation of canopy water content (CWC) for the whole USA. The slope between observed and estimated values was closer to 1 in our case (slope = 0.74, versus the Trombetti et al., 2008 values of 1.67). Therefore, the performance of our model is similar to theirs. However, Trombetti et al. (2008) used AVIRIS estimations of CWC as the validation dataset, and therefore it should expected higher accuracies, as AVIRIS outputs may be more comparable to MODIS than field data.

The estimations based on the MCD43A4 product (approach 2) were found more accurate than those based on the MOD09A1 (approach 1). This could be explained by two factors: on one hand, the second product is based on a shorter period (8 days versus 16 days), which implies noisier time series caused by clouds or other atmospheric effects (Yebra et al., 2013). On the other hand, reflectances from MCD43A4 are nadir corrected (Schaaf et al., 2002), so the observed reflectance is closer to our simulations that were based on zero zenith angles. For this reason, we recommend to use the MCD43A4 product for LFMC estimation, particularly when dealing with shrubs and trees, as they have a much higher temporal stability than grasslands in terms of moisture content. For the same reason, even though Terra and Aqua acquisitions are differed a few hours, the combination of these two sensors should not be problematic for LFMC retrieval, as the daily changes of moisture conditions for trees are minor with respect to the seasonal trends (Blackmarr and Flanner, 1968).

With regard to the introduction of auxiliary data, fixing LAI for the inversion did not improve our results (RMSE of 32.58% and 52.58% for the Mediterranean and the Eurosiberian regions, respectively). This was unexpected, since other studies focused on Mediterranean grassland and shrubland obtained more accurate results by fixing the LAI (RMSE of 24.6% and 19.8% for grassland and shrubland respectively: Yebra and Chuvieco, 2009b; Yebra et al., 2008b). Several authors concluded that the LAI product collection 4 derived from MODIS presented

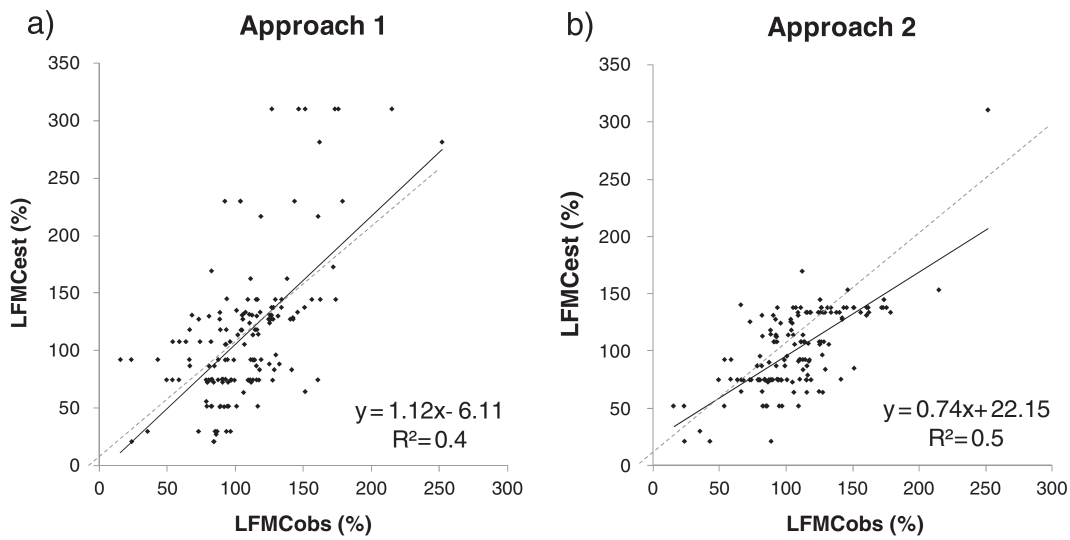

Fig. 6. Observed vs. estimated LFMC values across the validation sites using: a) MOD09A1 product (approach 1) and b) MCD43A4 product (approach 2). The option b) shows higher determination coefficient while option a) shows a slope closer to 1. Both models are statistically significant at 99% with *p*-values < 0.001.

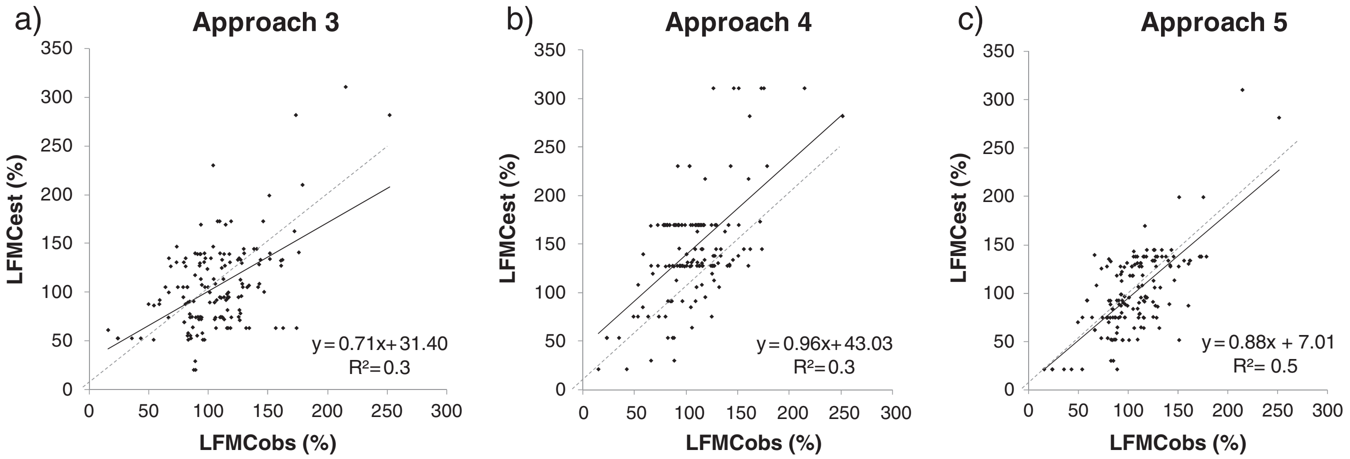

Fig. 7. Observed vs. estimated LFMC values across the validation sites using MCD43 product and fixing: a) LAI with MOD15A2 (approach 3), b) canopy coverage with MOD44B (approach 4) and c) canopy coverage with the product developed by Guerschman et al. (2009) (approach 5). All models are statistically significant at 99% with p-values < 0.001.

uncertainties especially concerning dense forests (Garrigues et al., 2008; Shabanov et al., 2005) so it may explain the worse results obtained especially in the Eurosiberian region where the canopy is characterized by higher LAI. As the mentioned authors explained, on one hand, a mismatch between simulated and measured MODIS surface reflectances (due to non-optimal selection of radiative transfer parameters, especially spectral leaf albedo) was found. On the other hand, it may be due to the high sensitivity of MODIS retrievals to surface reflectance uncertainties for large LAI. Collection 5 (which was used in the present study) tried to overcome these limitations. Even though a more extended validation of this product is required, it has been shown to include relevant errors (De Kauwe et al., 2011; Yebra et al., 2013).

Fixing ccov did not significantly improve the results neither. Using the MOD44B product in the models inversion tended to overestimate LFMC, possibly due to the underestimations of ccov parameter, especially in the Mediterranean region. The minimum, maximum and average ccov estimated by this product were 0.12, 0.55 and 0.36 in this region and 0.50, 0.80 and 0.70 for the Eurosiberian region. According to our experience and field observations, ccov values are higher in both regions. For example Yebra and Chuvieco (2009b) considered values of 0.4 in the Mediterranean region. The product developed by Guerschman et al. (2009) derived more similar values to those observed in field (minimum, maximum and average ccov of 0.48, 0.85 and 0.68, respectively in the Mediterranean region and 0.83, 1 and 0.92 in the Eurosiberian region). Even when using more accurate ccov estimations, the LFMC retrieval did not significantly improved (RMSE = 59.1% with the former ccov values, 31.1%with the latter ones and 27.7% without fixing ccov). Hence, fixing ccov did not solve any indetermination problem.

Several factors of uncertainty should be considered for future improvements of the model:

a) Our model was parameterized based on three representative species of each of the two ecoregions and they were inverted for pixels that may include other species. Whether the parameters are well adjusted to those additional species needs to be further tested.
b) Each MODIS pixel includes an area that is very difficult to sample on the ground. Any field measurement implies a certain level of error, particularly when target pixels include a wide field of view. The observed LFMC was computed with the average of three samples per plot. The standard deviations between ground samples were up to 20% in some cases (similar to what it was found by Yebra et al. (2008a) for grasslands ≈ 22%), and even reached 50% at the beginning and middle of the Spring season.
c) Another factor of uncertainty is the degree of mixtures within a MODIS pixel, as different species may include different LAI or fcov values. This is difficult to quantify considering the size of the study area (> 480,000 km^2).

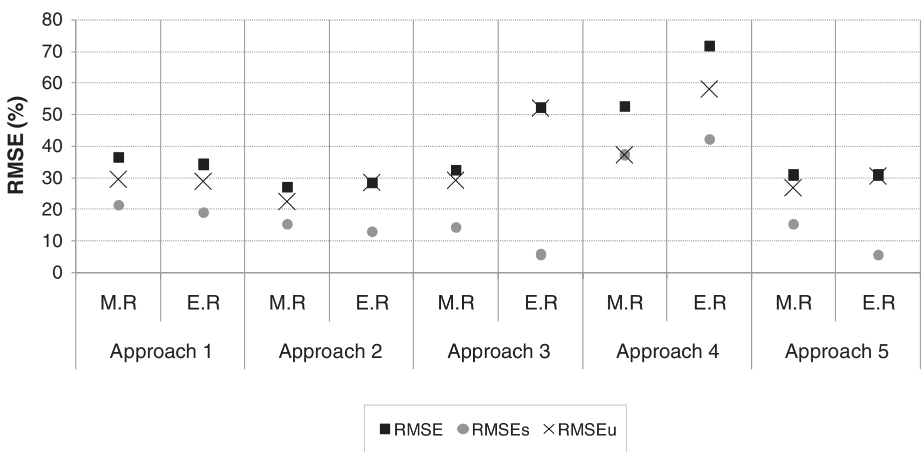

Fig. 8. Evaluation of the inversion of PROSPECT + GEOSAIL to estimate LFMC against observed LFMC over different regions (being M.R and E.R the Mediterranean and the Eurosiberian regions, respectively) for inversion approaches 1 to 5 (see Table 3). Total, systematic and unsystematic RMSE are shown.

d) Models were based on ecoregions, but they did not consider potential variations in seasonal trends. We observed that errors were in fact related to seasons, particularly in the Spring time, when more variability in moisture conditions was observed. In fact, when the Spring samples were discarded from the analysis, the RMSE decreased from 29 to 25.72% and from 30% to 26.58% for the Mediterranean and the Eurosiberian regions, respectively. The Summer season commonly presents the highest fire risk in Spain. However, a large number of fires occur in Spring too, particularly in the Eurosiberian region. Within the 1998 to 2007 period, 46% of all fires in this region occur during the Spring season (late March to late May) (http://www.magrama.gob.es/es/biodiversidad/temas/defensa-contra-incendios-forestales/estadisticas-de-incendios-forestales/default.aspx, last accessed January, 2012), so special attention should be paid to these periods in future works.
e) Model parameterization for this study was based on field and laboratory data. Yebra et al. (2008b, 2009a, 2009b) showed that species adapted parameters tend to provide more accurate estimations than random variations. However, parameters are always an approximation to reality, and the degree of similarity to real conditions is another factor of uncertainty. Site specific parameters could also be derived from ground or airborne lidar measurements, which have proven very accurate for estimating LAI, fcover and ccov (Drake et al., 2002; Means et al., 1999).

In spite of the relevance of these various factors of uncertainty, the estimation of LFMC from satellite images is very relevant for fire risk assessment, as this variable is difficult to obtain from meteorological variables or field campaigns. Even though, the moisture content of dead fuels is more relevant than live's in terms of fire ignition, several studies have shown that fire propagation and the detection of severe fire conditions are well associated with moisture conditions of live fuels, particularly for extended periods of droughts (Pierce et al., 2004; Ray et al., 2005; Siegert et al., 2001).

Our study was based on RTM models so, as they are not based on empirical relations, they can be applicable to other regions, particularly those with similar climate conditions to Spain, such as temperate forest in the Mediterranean Basin, in Western United States, Chile, Australia or South Africa.

5. Conclusions

The present work studied the performance of RTM to retrieve LFMC for woodlands by the use of the Look Up Table (LUT) inversion technique. The primary effort was put into the inclusion of ecological criteria in the RTM parameterization by an exhaustive exploration of data sources.

The novelty of our approach was the linked use of PROSPECT with GEOSAIL to estimate LFMC of needleaf and broadleaf woodlands. Two reflectance MODIS products were employed in the inversion from which the MCD43A4 showed the best results. We obtained results within the expected accuracy taking into account the large degree of uncertainty in the field measurements of LFMC used in the validation. The RMSE was 27.7% (27.3% and 28.7% for the Spanish Mediterranean-water limited and Eurosiberian-energy limited woodlands, respectively). In an attempt to find the maximum accuracy, LAI and ccov were fixed in the inversion using different remote sensing products. However, they did not improve the results.

The calibrated models were based on a priori knowledge of plant biophysical parameters in order to represent realistic situations. Consequently, the models presented in this study can be applied to other woodland areas without highly affecting the accuracy of the estimations. Future research should aim to test further enhancements in generalization with the aim of providing continental to global fuel moisture content estimations.

Acknowledgments

This research has been funded by the Spanish Ministry of Education and Science by means of the FPU grant program which supports Sara Jurdao, and supported by the FIREGLOBE project (CGL2008-01083), funded by the Spanish Ministry of Science and Technology. The LFMC sampling was also performed within the FIRERISK (AGL2000-0842-C04-01) and FIREMAP (CGL2004-060490C04-01/CLI) projects, both funded by the Spanish Commission for Science and Technology. The authors would also like to thank Valéry Gond (Department of Biology, University of Antwerpen, Belgium) and collaborators for providing the data of *Quercus robur* as well as Karen Barry (School of Agricultural Science, University of Tasmania, Australia) for her support with the *Eucalyptus globulus* data.

References

Barry, K. M., Newnham, G. J., & Stone, C. (2009). Estimation of chlorophyll content in *Eucalyptus globulus* foliage with the leaf reflectance model PROSPECT. *Agricultural and Forest Meteorology*, *149*, 1209–1213.
Blackmarr, W. H., & Flanner, W. B. (1968). *Seasonal and diurnal variation in moisture content of six species of Pocosin shrubs*. Asheville, North Carolina, USA: Southeastern Forest Experiment Station, USDA Forest Service.
Boerner, R. E. J., Huang, J., & Hart, S. C. (2009). Impacts of Fire and Fire Surrogate treatments on forest soil properties: a meta-analytical approach. *Ecological Applications*, *19*, 338–358.
Bowyer, P., & Danson, F. M. (2004). Sensitivity of spectral reflectance to variation in live fuel moisture content at leaf and canopy level. *Remote Sensing of Environment*, *92*, 297–308.
Burgan, R., Hartford, R., & Eidenshink, J. (1996). *Using NDVI to assess departure from average greenness and its relation to fire business*. Ogden, Utah: USDA Forest Service. Intermountain Research Station.
Castro, F. X., Tudela, A., Gabriel, E., Montserrat, D., Canyameres, E., & Segarra, M. (2006). Evolution of live fuel moisture in mediterranean forest. In D. X. Viegas (Ed.), *V International Conference on Forest Fire Research*. Elsevier: FIguera da Foz.
Ceccato, P. (2001). Estimation of vegetation water content using remote sensing for the assessment of fire risk occurrence and burning efficiency. *Phylosophy* (pp. 168). Ispra, Italy: University of Greenwich.
Ceccato, P., Gobron, N., Flasse, S., Pinty, B., & Tarantola, S. (2002). Designing a spectral index to estimate vegetation water content from remote sensing data: Part 1 Theoretical approach. *Remote Sensing of Environment*, *82*, 188–197.
Chuvieco, E., Aguado, I., Jurdao, S., Pettinari, M. L., Yebra, M., Salas, J., et al. (2012). Integrating geospatial information into fire risk assessment. *International Journal of Wildland Fire* (http://dx.doi.org/10.1071/WF12052).
Chuvieco, E., Aguado, I., Yebra, M., Nieto, H., Salas, J., Martín, M. P., et al. (2010). Development of a framework for fire risk assessment using remote sensing and geographic information system technologies. *Ecological Modelling*, *221*, 46–58.
Chuvieco, E., Cocero, D., Aguado, I., Palacios-Orueta, A., & Prado, E. (2004a). Improving Burning Efficiency Estimates through Satellite Assessment of Fuel Moisture Content. *Journal of Geophysical Research-Atmospheres*, *109*(D14S07), 1–8. http://dx.doi.org/10.1029/2003JD003467.
Chuvieco, E., Cocero, D., Riaño, D., Martín, M. P., Martínez-Vega, J., de la Riva, J., et al. (2004b). 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.
Chuvieco, E., González, I., Verdú, F., Aguado, I., & Yebra, M. (2009a). Prediction of fire occurrence from live fuel moisture content measurements in a Mediterranean ecosystem. *International Journal of Widland Fire*, *18*, 430–441.
Chuvieco, E., Riaño, D., Aguado, I., & Cocero, D. (2002). Estimation of fuel moisture content from multitemporal analysis of Landsat Thematic Mapper reflectance data: applications in fire danger assessment. *International Journal of Remote Sensing*, *23*, 2145–2162.
Chuvieco, E., Wagtendonk, J., Riaño, D., Yebra, M., & Ustin, S. L. (2009b). Estimation of Fuel Conditions for Fire Danger Assessment. In E. Chuvieco (Ed.), *Earth Observation of Wildland Fires in Mediterranean Ecosystems* (pp. 83–96). New York: Springer.
Chuvieco, E., Yebra, M., Jurdao, S., Aguado, I., Salas, J., García, M., et al. (2011). *Field fuel moisture measurements on Spanish study sites*. Department of Geography, University of Alcalá (http://www.geogra.uah.es/emilio/FMC_UAH.html)
Colombo, R., Meroni, M., Marchesi, A., Busetto, L., Rossini, M., Giardino, C., et al. (2008). Estimation of leaf and canopy water content in poplar plantations by means of hyperspectral indices and inverse modeling. *Remote Sensing of Environment*, *112*, 1820–1834.
Combal, B., Baret, F., Weiss, M., Trubuil, A., Mace, D., Pragnère, A., et al. (2002). Retrieval of canopy biophysical variables from bidirectional reflectance Using prior information to solve the ill-posed inverse problem. *Remote Sensing of Environment*, *84*, 1–15.
Conard, S. G., & Solomon, A. M. (2008). Effects of wildland fire on regional and global carbon stocks in a changing environment. *Developments in Enviromental Sciences*, *8*.
Danson, F. M., & Bowyer, P. (2004). Estimating live fuel moisture content from remotely sensed reflectance. *Remote Sensing of Environment*, *92*, 309–321.

Danson, F. M., Steven, M. D., Malthus, T. J., & Clark, J. A. (1992). High-spectral resolution data for determining leaf water content. *International Journal of Remote Sensing*, *13*, 461–470.

De Groot, W. J., Wardati, & Wang, Y. (2005). Calibrating the Fine Fuel Moisture Code for grass ignition potential in Sumatra, Indonesia. *International Journal of Widland Fire*, *14*, 161–168.

De Kauwe, M. G., Disney, M. I., Quaife, T., Lewis, P., & Williams, M. (2011). An assessment of the MODIS collection 5 leaf are index product for a region of mixed coniferous forest. *Remote Sensing of Environment*, *115*, 767–780.

De Santis, A., & Chuvieco, E. (2007). Burn severity estimation from remotely sensed data: performance of simulation versus empirical models. *Remote Sensing of Environment*, *108*, 422–435.

De Santis, A., Chuvieco, E., & Vaughan, P. J. (2009). Short-term assessment of burn severity using the inversion of PROSPECT and GeoSail models. *Remote Sensing of Environment*, *113*, 126–136.

De Santis, A., Vaughan, P., & Chuvieco, E. (2006). Foliage moisture content estimation from 1-D and 2-D spectroradiometry for fire danger assessment. *Journal of Geophysical Research, Biosciences*, *111*. http://dx.doi.org/10.1029/2005JG000149.

Dennison, P. E., Moritz, M. A., & Taylor, R. S. (2008). Evaluating predictive models of critical live fuel moisture in the Santa Monica mountains, California. *International Journal of Wildland Fire*, *17*, 18–27.

Dennison, P. E., Roberts Dar, A., Peterson, S. H., & Rechel, J. (2005). Use of Normalized Difference Water Index for monitoring live fuel moisture content. *International Journal of Remote Sensing*, *26*, 1035–1042.

Drake, J. B., Dubayah, R. O., Clark, D. B., Knox, R. G., Blair, J. B., Hofton, M. A., et al. (2002). Estimation of tropical forest structural characteristics using large-footprint lidar. *Remote Sensing of Environment*, *79*, 305–319.

Dufrêne, E., & Bréda, N. (1995). Estimation of deciduous forest leaf area index using direct and indirect methods. *Oecologia*, *104*, 156–162.

Garcia, M., Aguado, I., & Chuvieco, E. (2008). Combining AVHRR and meteorological data for estimating live fuel moisture content in forest fire danger rating. *Remote Sensing of Environment*, *112*, 3618–3627.

Garrigues, S., Lacaze, R., Baret, F., Morisette, J. T., Weiss, M., Nickeson, J. E., et al. (2008). Validation and intercomparison of global Leaf Area Index products derived from remote sensing data. *Journal of Geophysical Research*, *113*.

Gond, D. V., De Pury, D. G. G., Veroustraete, F., & Ceulemans, R. (1999). Seasonal variations in leaf area index, leaf chlorophyll, and water content; scaling-up to estimate fAPAR and carbon balance in a multilayer, multispecies temperate forest. *Tree Physiology*, *19*, 673–679.

Guerschman, J. P., Hill, M. J., Renzullo, L. J., Barret, D. J., Marks, A. S., & Botha, E. J. (2009). Estimating fractional cover of photosynthetic vegetation, non-photosynthetic vegetation and bare soil in the Australian tropical savanna region upscaling the EO-1 Hyperion and MODIS sensors. *Remote Sensing of Environment*, *113*, 928–945.

Hansen, M. C., DeFries, R. S., Townshend, J. R. G., Carroll, M., Dimiceli, C., & Sohlberg, R. A. (2001). Vegetation Continuous Fields MOD44B. *2001 Percent Tree Cover, Collection 4*. Maryland: University of Maryland, College Park.

Hansen, M. C., DeFries, R. S., Townshend, J. R. G., Carroll, M., Dimiceli, C., & Sohlberg, R. A. (2003). Global Percent Tree Cover at a Spatial Resolution of 500 Meters: First Results of the MODIS Vegetation Continuous Fields Algorithm. *Earth Interactions*, *7*, 1–15.

Hardisky, M. A., Klemas, V., & Smart, R. M. (1983). The influence of soil salinity, growth form, and leaf moisture on the spectral radiance of *Spartina alterniflora* canopies. *Photogrammetric Engineering and Remote Sensing*, *49*, 77–83.

Hardy, C. C., & Burgan, R. E. (1999). Evaluation of NDVI for monitoring live moisture in three vegetation types of the Western U.S. *Photogrammetric Engineering and Remote Sensing*, *65*, 603–610.

Huemmrich, K. F. (2001). The GeoSail model: a simple addition to the SAIL model to describe discontinuous canopy reflectance. *Remote Sensing of Environment*, *75*, 423–431.

Hytteborn, H. (1975). Deciduous woodland at Andersby, eastern Sweden: Above-ground tree and shrub production. *Acta Phytogeographica Suecica*, *61*, 1–96.

Jacquemoud, S. (1990). PROSPECT: a model to leaf optical properties spectra. *Remote Sensing of Environment*, *34*, 74–91.

Jurdao, S., Oliva, P., Yebra, M., & Chuvieco, E. (2012). Estudio de la influencia del estrés hídrico en la reflectividad y en determinados parámetros de la hoja. Ensayo experimental con *Pinus halepensis* Mill. *XV Congreso Nacinal Tecnologías de Información Geográfica. Las tecnologías de la Información Geográfica en el contexto de Cambio Global. Madrid. Spain.*

Kilgore, B. M. (1973). The ecological role of fire in Sierran conifer forests: Its application to National Park management. *Quaternary Research*, *3*, 496–513.

Kimes, D., Knyazikhin, Y., Privette, J. L., Abuelagasim, A. A., & Gao, F. (2000). Inversion methods for physically based models. *Remote Sensing Reviews*, *18*, 381–439.

Knyazikhin, Y., Knyazikhin, Y., Glassy, J., Privette, J. L., Tian, Y., Lotsch, A., et al. (1999). *MODIS Leaf Area Index (LAI) And Fraction Of Photosynthetically Active Radiation Absorbed By Vegetation (FPAR) Product (MOD15)*. Algorithm Theoretical Basis Document (ttp://eospso.gsfc.nasa.gov/atbd/modistables.html).

Kötz, B., Schaepmanb, M., Morsdorf, F., Bowyer, P., Ittena, K., & Allgöwer, B. (2004). Radiative transfer modeling within a heterogeneous canopy for estimation of forest fire fuel properties. *Remote Sensing of Environment*, *92*, 332–344.

Kruse, F. A., Lefkoff, A. B., Boardman, J. B., Heidebrecht, K. B., Shapiro, A. T., Barloon, P. J., et al. (1993). The Spectral Image Processing (SIPS) — Interactive Visualization and Analysis of Imaging Specrometer Data. *Remote Sensing of Environment*, *44*, 145–163.

Le Dantec, V., Dufrêne, E., & Saugier, B. (2000). Interanual and spatial variation in maximum leaf area index of temperate deciduous stands. *Forest Ecology and Management*, *134*, 71–81.

Liang, S. (2004). *Quantitative remote sensing for land surface characterization*. Hoboken, NJ: Wiley.

López, F. R., del Cerro, A., Abellán, M. A., Briongos, J. M., & García, F. A. (2000). Estimación directa (alométrica) del LAI de una masa de *Pinus halepensis*. *Variabilidad de la relación alométrica "área foliar vs. diámetro normal". Cuad. Soc. Esp. Cien. For.*, *10*. (pp. 147–155).

Means, J. E., Acker, S. A., Harding, D. J., Blair, J. B., Lefsky, M. A., Cohen, W. B., et al. (1999). Use of large-footprint scanning airborne lidar to estimate forest stand characteristics in the Western Cascades of Oregon. *Remote Sensing of Environment*, *67*, 298–308.

Myneni, R., Running, S. W., Glassy, J., & Votava, P. (2000). FPAR, LAI User's Guide. (ESDT: MOD15A2) 8-day Composite NASA MODIS Land Algorithm. In Terra MODIS Land Team(Ed.).

Pellizaro, G., Cesaraccio, C., Duce, P., Ventura, A., & Zara, P. (2007). Relationships between seasonal patterns of live fuel moisture and meteorological drought indices for Mediterranean shrubland species. *International Journal of Widland Fire*, *16*, 232–241.

Peterson, S., Roberts, D.A., & Dennison, P.E. (2008). Mapping live fuel moisture with MODIS data: a multiple regression approach. *Remote Sensing of Environment*, *En revisión*.

Pierce, J. L., Meyer, G. A., & Jull, A. J. T. (2004). Fire-induced erosion and millennial scale climate change in northern ponderosa pine forests. *Nature*, *432*, 87–90.

Ray, D., Nepstad, D., & Moutinho, P. (2005). Micrometeorological and canopy controls of fire susceptibility in a forested Amazon landscape. *Ecological Applications*, *15*, 1664–1678.

Riaño, D., Ustin, S. L., Usero, L., & Patricio, M. A. (2005a). Estimation of fuel moisture content using neural networks. *Artificial Intelligence and Knowledge Engineering Applications: A Bioinspired Approach, Pt 2, Proceedings*, *3562*, 489–498.

Riaño, D., Valladares, F., Condés, S., & Chuvieco, E. (2004). Estimation of leaf area index and covered ground from airborne laser scanner (Lidar) in two contrasting forests. *Agricultural and Forest Meteorology*, *124*, 269–275.

Riaño, D., Vaughan, P., Chuvieco, E., Zarco-Tejada, P., & Ustin, S. L. (2005b). Estimation of Fuel Moisture Content by Inversion of Radiative Transfer Models to Simulate Equivalent Water Thickness and Dry Matter Content: Analysis at Leaf and Canopy Level. *IEEE Transactions on Geoscience and Remote Sensing*, *43*, 819–826.

Rivas Martínez, S. (1983). Pisos bioclimáticos de España. *Lazaroa*, *5*, 33–43.

Roberts, D. A., Peterson, S., Dennison, P. E., Sweeney, S., & Rechel, J. (2006). Evaluation of Aibone Visible/Infrared Imaging Spectrometer (AVIRIS) and Moderate Resolution Imaging Spectrometer (MODIS) measures of live fuel moisture and fuel condition in a shrubland ecosystem in southern California. *Journal of Geophysical Research*, *111*(GO4S02). http://dx.doi.org/10.1029/2005JG000113.

Sandberg, D. V., Ottmar, R. D., Peterson, J. L., & Core, J. (2002). Wildland fire on ecosystems: Effects of Fire on Air. Ogden, UT: U.S.: Department of Agriculture, Forest Service, Rocky Mountain Research Station.

Schaaf, C. B., Gao, F., Strahler, A. H., Lucht, W., Li, X., Tsang, T., et al. (2002). First operational BRDF, albedo nadir reflectance products from MODIS. *Remote Sensing of Environment*, *83*, 135–148.

Shabanov, N. V., Huang, D., Yang, W. Z., Tan, B., Knyazikhin, Y., Myneni, R. B., et al. (2005). Analysis and optimization of the MODIS leaf area index algorithm retrievals over broadleaf forests. *IEEE Transactions on Geoscience and Remote Sensing*, *43*, 1855–1865.

Siegert, F., Rücker, G., Hinrichs, A., & Hoffmann, A. (2001). Increased damage from fires in logged forests during droughts caused by El Niño. *Nature*, *414*, 437–440.

Silla, F., González-Gil, A., González-Molina, M. E., Mediavilla, S., & Escudero, A. (2010). Estimation of chlorophyll in *Querqus* leaves using a portable chlorophyll meter: effects of species and leaf age. *Annals of Forest Science*, *67*.

Trombetti, M., Riano, D., Rubio, M. A., Cheng, Y. B., & Ustin, S. L. (2008). Multi-temporal vegetation canopy water content retrieval and interpretation using artificial neural networks for the continental USA. *Remote Sensing of Environment*, *112*, 203–215.

Valladares, F. (2004). *Ecología del bosque mediterráneo en un mundo cambiante*. Madrid, Spain: Ministerio de Medio Ambiente, EGRAF, S. A.

van der Werf, G. R., Morton, D. C., DeFries, R. S., Olivier, J. G. J., Kasibhatla, P. S., Jackson, R. B., et al. (2009). CO2 emissions from forest loss. *Nature Geoscience*, *2*, 737–738.

van der Werf, G. R., Randerson, J. T., Giglio, L., Collatz, G. J., Kasibhatla, P. S., & Arellano, A. F. (2006). Interannual variability in global biomass burning emissions from 1997 to 2004. *Atmospheric Chemistry and Physics*, *6*, 3423–3441.

Verhoef, W. (1984). Light scattering by leaf layers with application to canopy reflectance modeling: the SAIL model. *Remote Sensing of Environment*, *16*, 125–141.

Vermote, E. F., & Vermeulen, A. (1999). Atmospheric correction algorithm: Spectral Reflectances (MOD09), ATDB version 4.0. NASA.

Viegas, D. X., Viegas, T. P., & Ferreira, A. D. (1992). Moisture content of fine forest fuels and fire occurrence in central Portugal. *International Journal of Wildland Fire*, *2*, 69–85.

Ward, D. E., Hao, W. M., Susott, R. A., Babbitt, R. E., Shea, R. W., Kauffman, J. B., et al. (1996). Effect of fuel composition on combustion efficiency and emission factors for African savanna ecosystems. *Journal of Geophysical Research*, *101*, 23569–23576.

Weiss, M., Baret, F., Myneni, R. B., Pragnère, A., & Knyazikhin, Y. (2000). Investigation of a model inversion technique to estimate canopy biophysical variables from spectral and directional reflectance data. *Agronomie*, *20*, 3–22.

Wellburn, A. R. (1994). The Spectral Determination of Chlorophylls a and b, as well as Total Carotenoids, Using Various Solvents with Spectrophotometers of Different Resolution. *Journal of Plant Physiology*, *144*, 307–313.

Willmott, C. J. (1982). Some Comments on the Evaluation of Model Performance. *Bulletin of the American Meteorological Society*, *63*, 1309–1313.

Yebra, M., & Chuvieco, E. (2008). Modelos de Simulación de Reflectividad en ecología: potencialidades y problemas. *Ecosistemas*, *17*, 23–28.

Yebra, M., & Chuvieco, E. (2009a). Generation of a Species-Specific Look-Up Table for Fuel Moisture Content Assessment. *IEEE JSTARS*, *2*, 21–26.

Yebra, M., & Chuvieco, E. (2009b). Linking ecological information and radiative transfer models to estimate fuel moisture content in the Mediterranean region of Spain: Solving the ill-posed inverse problem. *Remote Sensing of Environment*, *113*, 2403–2411.

Yebra, M., Chuvieco, E., & Aguado, I. (2008a). Comparación de modelos empíricos y de transferencia radiativa para estimar contenido de humedad en pastizales: Poder de generalización. *Revista de teledetección*, *29*, 73–90.

Yebra, M., Chuvieco, E., & Riaño, D. (2008b). Estimation of live Fuel Moisture Content from MODIS images for fire risk assessment. *Agricultural and Forest Meteorology*, *148*, 523–536.

Yebra, M., Van Dijk, A. I. J. M., Leuning, R., Huete, A. R., & Guerschman, J. P. (2013). Evaluation of optical remote sensing to estimate actual evapotranspiration and canopy conductance. *Remote Sensing of Environment*, *129*, 250–261.

Zarco-Tejada, P. J., Rueda, C. A., & Ustin, S. L. (2003). Water content estimation in vegetation with MODIS reflectance data and model inversion methods. *Remote Sensing of Environment*, *85*, 109–124.

Zylstra, P. (2011). Forest flammability: modelling and managing a complex system. *School of Physical, Environmental and Mathematical Sciences* (pp. 435). Canberra: The University of New South Wales Australian Defence Force Academy.