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

David Riaño, Patrick Vaughan, Emilio Chuvieco, Pablo J. Zarco-Tejada, and Susan L. Ustin, *Senior Member, IEEE*

***Abstract*—Fire danger models identify fuel moisture content (FMC) of live vegetation as a critical variable, since it affects fire ignition and propagation. FMC can be calculated by dividing equivalent water thickness (EWT) by dry matter content (DM). The "leaf optical properties spectra" (PROSPECT) model was inverted to estimate EWT and DM separately using the Leaf Optical Properties Experiment (LOPEX) database, based on 490 measurements of leaf optical and biochemical properties. DM estimations were poor when leaf samples were fresh ($r^2 = 0.38$). Results of a sensitivity analysis conducted on the spectral response of samples demonstrated that water absorption masks the effects of DM on the spectral response. This causes a poor estimation of FMC ($r^2 = 0.33$), even though EWT estimation was good ($r^2 = 0.94$). However, DM of dry samples was accurately estimated ($r^2 = 0.84$), since no water was present. FMC estimation in fresh leaf material improved considerably ($r^2 = 0.89$) by accounting for DM in fresh samples ($r^2 = 0.71$), when a constant species-dependent DM value is used. A similar approach was taken on a canopy level by linking the PROSPECT leaf model with the Lillesaeter infinitive reflectance canopy model using data from laboratory measurements under controlled conditions. As expected, results indicate grater difficulty to estimate DM and FMC on a canopy level, although similar trends were observed. DM estimation improved from $r^2 = 0.12$ to $r^2 = 0.39$ when considering measurements of dry samples, which when used for FMC estimation, correlations increase from $r^2 = 0.62$ to $r^2 = 0.81$. Therefore, DM can be accurately estimated only when plant material is dry, and it is a necessary measurement in order to estimate FMC accurately. DM remains stable over annual time periods although lower values are expected during the drought season. However, time variations in DM are smaller than DM variations among species. Because there is also a decrease in water content with low EWT values during phenologically dormant periods, multitemporal data could be used to estimate FMC. Further research must be applied on real canopies to confirm these results.**

***Index Terms*—Dry matter (DM), equivalent water thickness (EWT), fire danger, fuel moisture content (FMC), infinite reflectance, model inversion, radiative transfer.**

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D. Riaño was with the Center for Spatial Technologies and Remote Sensing, University of California, Davis, CA 95616-8617 USA and is now with the Department of Geography, University of Alcalá, Madrid 28801, Spain (e-mail: driano@cstars.ucdavis.edu).

P. Vaughan and E. Chuvieco are with the Department of Geography, University of Alcalá, Madrid 28801, Spain (e-mail: villalukas@yahoo.co.uk; emilio.chuvieco@uah.es).

Pablo J. Zarco-Tejada is with the Institute for Sustainable Agriculture (IAS), Spanish Council for Scientific Research (CSIC), 14004 Córdoba, Spain (e-mail: pzarco@ias.csic.es).

Susan L. Ustin is with the Center for Spatial Technologies and Remote Sensing, University of California, Davis, CA 95616-8617 USA (e-mail: susan@cstars.ucdavis.edu).

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I. INTRODUCTION

FUEL moisture content (FMC) of live vegetation is often used to predict fire danger, since the amount of water per unit dry matter is critical to both fire ignition and fire propagation predictors [1]. Traditional means of measuring FMC are based on field sampling and meteorological danger indices [2]. Remote sensing can provide the spatial and temporal coverage needed for FMC, in order to integrate it in fire danger models.

Empirical methods commonly based on statistical fitting techniques have been used to estimate FMC [3]–[7]. These techniques have the advantage of being applicable to a large temporal dataset once the model is built and have a known accuracy. The disadvantage is that index-derived empirical relationships are difficult to extrapolate for regional or global scale studies due to differences in leaf and canopy characteristics.

Several authors have shown that equivalent water thickness (EWT) relates better to spectral measurements than to FMC [8]–[11], since it is directly related to water absorption depth of leaves and therefore does not depend on dry matter content (DM). Since FMC is the amount of water per unit of dry matter, this parameter could be estimated from EWT and DM by the inversion of radiative transfer models [12]. Equations (1)–(3) show the calculation of EWT, DM, and FMC and their interrelations

$$\mathrm{EWT}\left(\frac{g}{\mathrm{cm}^2}\right) = \frac{W_f - W_d}{A} \tag{1}$$

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

$$\mathrm{FMC}(\%) = \frac{W_f - W_d}{W_d} * 100 = \frac{\mathrm{EWT}}{\mathrm{DM}} * 100 \tag{3}$$

where W_f = fresh leaf weight, W_d = dry leaf weight, and A = leaf area.

The inversion of radiative transfer models can provide a physical estimation of EWT and DM, providing more generalization power than empirical fittings. Although intensive computing is required, they can be applied to broader scales fixing input leaf and canopy variables as a function of the species where the inversion is conducted. Physical models, such as PROSPECT [12] can provide results on a leaf level for broadleaves or the model "leaf incorporating biochemicals exhibiting reflectance and transmittance yields" (LIBERTY) [13] for needles; and these can be linked with vegetation canopy models, such as the model "light scattering by leaf layers with application to canopy reflectance modeling" (SAILH) for infinite turbid-medium canopy simulations. These models are successfully used to estimate EWT; however, they fail to estimate DM when samples are fresh [14]. Fourty and Baret [15] in a simulation study explained that EWT is easier to estimate than DM due to more specific absorption features of water. EWT relates to FMC [16], considering species with similar DM are taken into account [17].

Similar problems are found in empirical approaches to obtain FMC. Different statistical relationships are found as a function of species [5], although some attempts have accounted for relationships among different species [17] using the multitemporal variation of normalized difference vegetation index (NDVI) and surface temperature. Estimations are also better when vegetation is drier [10].

The work presented here explores the estimation of FMC by inversion of PROSPECT leaf model, and when coupling PROSPECT to an infinitive reflectance model developed for stacked leaves [18]. Currently, FMC estimations have proven difficult for different species; and inversion of radiative transfer models has only been successful in estimating EWT. We propose to estimate FMC with DM estimated from dry measurements which is then used to obtain DM values of fresh leaves, assuming that DM is species-dependent [19]. Correlation of EWT and DM with reflectance and transmittance was tested using real data to evaluate whether any model could potentially estimate these factors. Sensitivity analysis of the models to changes in EWT and DM was previously performed but using only simulated data [8], [20].

II. Methods

A. Analysis of FMC at Leaf Level

1) Leaf Material: The Leaf Optical Properties Experiment (LOPEX) dataset was produced during an experiment conducted by the Joint Research Center (JRC) of the European Commission (Ispra, Italy) [21]. This dataset included measurements of different biochemical constituents and spectra of a wide sample of leaves. A total of 120 samples were collected in an area within 50 km range of the JRC, in Ispra. We selected 49 broad leaves samples for which the required leaf properties for our research purposes were measured: reflectance and transmittance of five fresh and five near-dry leaves (not completely dry, average EWT $= 0.000\,231$ g/cm^2, maximum EWT $= 0.001$ g/cm^2), EWT, and DM. Since some species were sampled more than once, this made a total of 245 fresh and 245 dry leaf measurements from 37 different species.

The contribution of different factors to DM variance enabled the study of DM variation within species. Three variance components were studied: 1) the state of the samples (fresh/dry); 2) interspecific variation; and 3) intraspecific variation. Restricted maximum likelihood [22] was applied for the estimation of these sources of variance using the function VARCOMP in S-PLUS 6.2.[1] This type of analysis is similar to an ANOVA, with the advantage of providing unbiased results for unbalanced experiments with some species having different number of samples, and for nonhomogeneous variances between species.

TABLE I
VARIANCE COMPONENTS (PERCENT, RESTRICTED MAXIMUM LIKELIHOOD) OF DM FOR LOPEX DATA, 245 FRESH AND 245 DRY LEAVES FROM 37 DIFFERENT SPECIES

	Variance (%)
Species	79.4
Leaf	16.0
State (fresh/dry)	4.5

We also analyzed the relationship between reflectance and transmittance for each wavelength according to EWT and DM, for fresh and dry leaf samples using correlation (r^2). Other factors, such as chlorophyll content or the internal structure parameter were not considered.

2) PROSPECT Model Inversion: Leaf structural and biochemical constituents were simulated inverting the PROSPECT model [12] based on leaf reflectance and transmittance. The PROSPECT version was updated using LOPEX [14]. The inversion was performed searching for each of the following parameters: leaf internal structure 1–4, leaf chlorophyll $a + b$ content 0–90 μg/cm^2, EWT 0–0.07 g/cm^2, DM 0–0.02 g/cm^2. A wide range of leaf chemistries was selected to include the greatest extent of possible values in our LOPEX dataset. The best fit was found minimizing the error over the whole spectrum between measured and simulated reflectance and transmittance, as used by Jacquemoud *et al.* [14].

The simulated EWT and DM quotient of each fresh leaf was compared to the actual FMC value. As will be shown later, the simulated FMC had large errors because of the poor estimation of DM. The simulated DM of dry leaves was taken into account instead of the simulated DM of fresh leaves in order to improve this result based on the assumptions that a typical DM value could be used to represent each species, and that DM does not change when samples are dried. Therefore, we derived DM for each species from the average of the simulated DM of all dry leaves for that species. The simulated DM for each species was compared to the actual DM measured for each fresh leaf. Finally, the quotient between the simulated EWT of each fresh leaf and the simulated DM for that species was correlated against the actual FMC of each fresh leaf. DM values for the species used in this paper probably could not be applied to other sites, since environmentally controlled variation is usually significant [23].

B. Analysis at Canopy Level of FMC

1) Vegetation Samples: The laboratory experiment consisted of a series of spectroradiometric measurements of three distinct Mediterranean species: gall oak (*Quercus pyrenaica* Willd), rosemary (*Rosmarinus oficinalis* L.), and rock rose (*Cistus ladanifer* L.). Each of these species is a good representative of the three main strategies that Mediterranean

[1]Insightful Corporation. See www.splus.com.

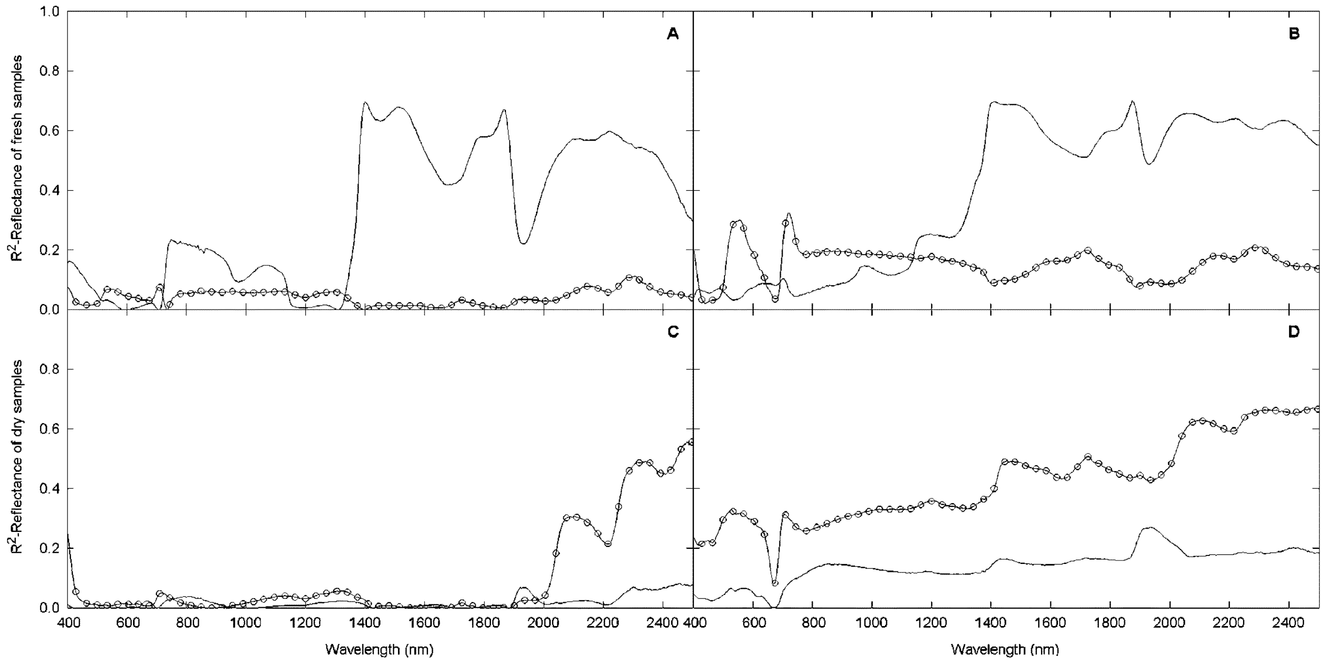

Fig. 1. Correlation r^2 between reflectance [(A) fresh samples, (C) dry samples] or transmittance [(B) fresh samples, (D) dry samples] and (line) EWT or (line with circles) DM for LOPEX data, 245 fresh and 245 dry leaves from 37 different species.

plants follow in order to survive the severe summer droughts in Spain's Central Plateau: endure, avoid, and resist [24], [25]. Gall oak avoids water stress mainly due to its large and deep rooted system, and also has smaller thicker leaves than other temperate *Quercus* species; rosemary is an endurer that reduces evapotranspiration thanks to its narrow side-curved leaf blades, with thick cuticles and sunken stomata; rock rose is a common and extended postfire colonizer that has a somewhat unique strategy, since it resists water stress partly by means of sticky laudanum oils that protect the cuticle and also has the side-effect of retarding the growth of other nearby species [26].

As a result of the distinct physiological features of the three species, different deterioration and water loss rates were expected throughout the leaf drying process that was to follow, and accordingly, so were their spectral responses.

2) Laboratory Measurements: Leaves of the above-referred species were measured with a GER 2600 Spectroradiometer (Geophysical & Environmental Research Corporation, Millbrook, NY) with a 400–2500-nm range, calibrated against a Labsphere Spectralon (Labsphere, Inc. North Sutton, NH) reference panel and a 1000-W halogen quartz lamp illuminating samples at 45°.

Leaf samples of each species were aligned (tiled array) on 18 cm $\times$ 15 cm trays, which were bound with three thin coal-stained strings to prevent leaf geometry changes and stress-induced shading effects from leaf curling. Leaf area, extracted by having previously scanned the leaves (200 dpi), and stacked-leaf layer areas were used to compute the resulting leaf area index (LAI) dividing the total leaf area by the tray area, gall oak $=$ 2.7, rosemary $= 3$ and rock rose $= 3.1$. Given the variety of leaf sizes and behavior under heat conditions a high LAI was necessary to avoid the influence of background reflectance from the tray surface (coal-paper coated), which would appear as leaves shrunk in size with water loss. Measurements were taken inside a coal paper-coated measuring box (aproximately size 1.5 m^3), which provided $<3\%$ background reflectance throughout the spectral range mentioned.

Leaf samples were collected early in the morning to ensure maximum moisture conditions [24], then placed in a cooler and measured within 1–2 h. Prior to each reflectance measurement, the trays containing the samples were weighed. Between measurements, the trays were placed in an oven at 50 °C. Higher oven temperatures were disregarded in order to follow more closely the already rapid effects of heat and water loss on reflectance and cell structure deterioration, and also to better simulate Mediterranean summer conditions. This process was repeated until the weight loss of each tray was zero; hence the species were completely dry.

3) PROSPECT–Lillesaeter Model Inversion: Canopy reflectance measurements from our laboratory experiment were used to simulate EWT and DM by inverting the PROSPECT model, which was linked with a simple infinite reflectance model developed by Lillesaeter [18], where canopy reflectance (ρ_{canopy}) was calculated as

$$\rho_{\text{canopy}} = \frac{\rho}{1-\tau^2} \tag{4}$$

where ρ is leaf reflectance and τ is leaf transmittance.

This model was selected because it was specifically designed for deriving canopy reflectance of stacked leaves, such as in our case. The best fit was found to be the same as for the leaf-level analysis, and the ranges for the parameters, again covering all possible values in our dataset, were: 1) leaf internal structure 0.5–4; 2) leaf chlorophyll $a+b$ content 0–60 μg/cm^2; 3) EWT 0–0.08 g/cm^2; and 4) DM 0–0.04 g/cm^2.

The simulated EWT and DM quotients of each laboratory spectral measurement were compared to the actual FMC values. The average of the simulated DM of dry samples for

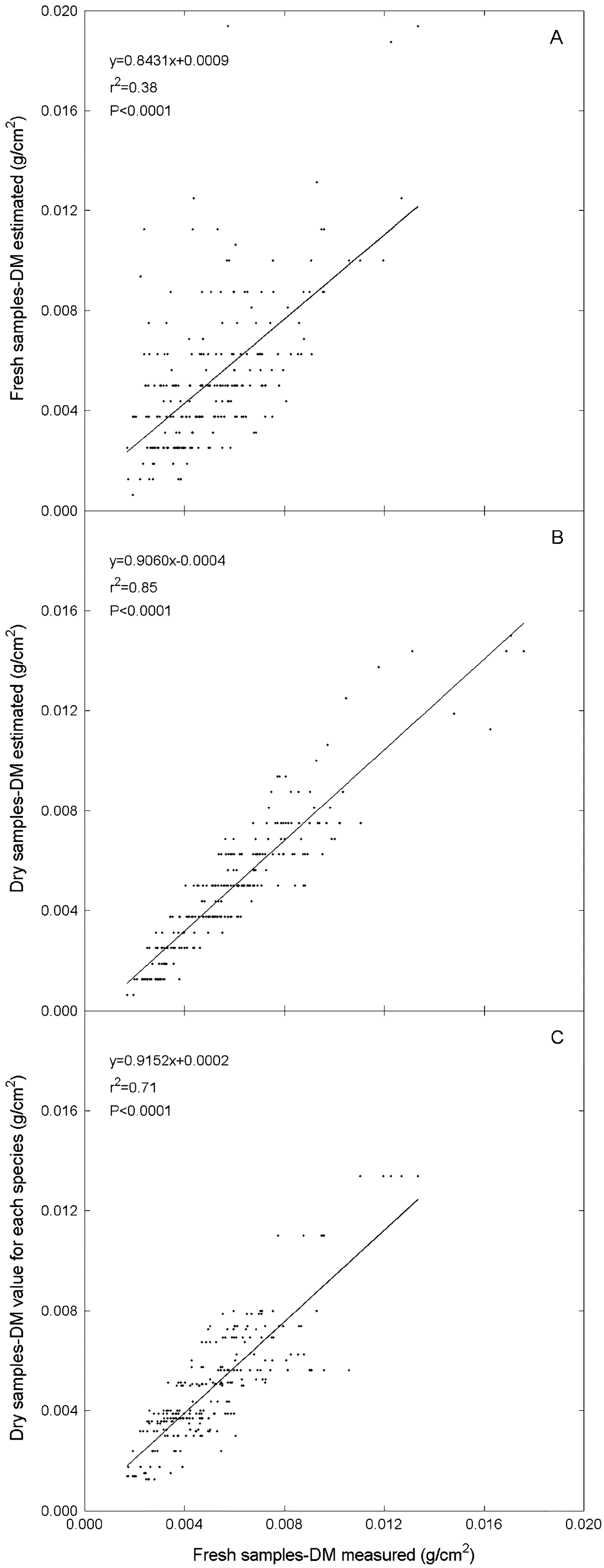

Fig. 2. DM estimation at leaf level for LOPEX data ($n = 245$), for (A) fresh samples, for (B) dry samples, and (C) for fresh samples based on the average of the simulated DM of dry samples for each species.

each species was also taken account to try to improve the DM estimation. Samples were considered dry when FMC $< 75\%$.

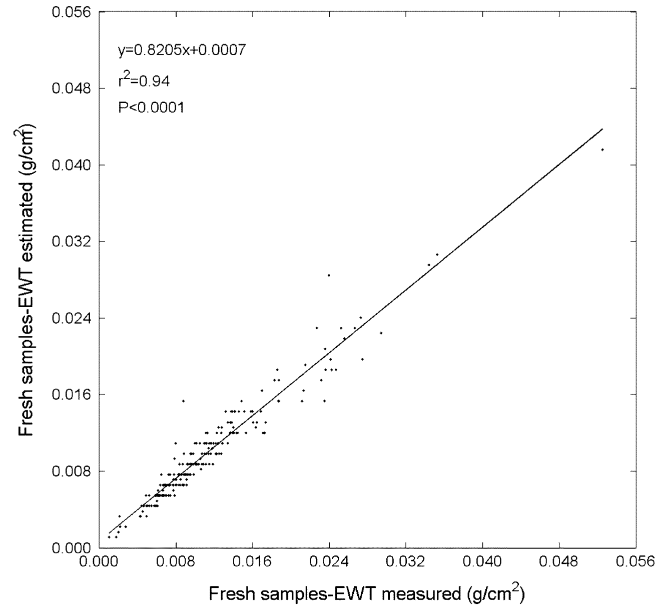

Fig. 3. EWT estimation at leaf level using fresh samples of LOPEX data ($n = 245$).

This value was selected based on the range of FMC values for this type of species during summer drought conditions [7].

III. Results

A. Analysis at Leaf Level of FMC

The LOPEX dataset showed that interspecific differences accounted for most of DM variance (Table I). On the other hand, neither leaves of the same species nor the analysis of dry versus fresh samples contributed much to the DM variance.

As expected, EWT was highly correlated with reflectance and transmittance of fresh leaves, especially in the shortwave infrared (SWIR), between 1400 and 2500 nm (Fig. 1). DM was highly correlated, especially with transmittance of dry samples, but low correlation was observed with fresh samples. Reflectance of dry samples was poorly correlated with both EWT and DM, being for the latter a little bit better in the region 2000–2500 nm.

The PROSPECT model inversion for the estimation of DM (Fig. 2) based on both reflectance and transmittance provided good results for the dry samples ($r^2 = 0.85$), but was less successful for the fresh samples ($r^2 = 0.38$). DM for fresh samples was successfully estimated using an average simulated DM value for each species extracted from dry samples ($r^2 = 0.71$). This last approach was possible, since interspecific differences contributed to most of the DM variance. The resulting equations for the prediction of DM were close to a 1 : 1 relationship and statistically significant (P-value <0.0001) in all cases. The steps in Fig. 2, with equal DM value estimated, were due to running the inversion every 0.0005 g/cm^2. Higher precision could have eliminated these steps, but this would have been computationally very expensive.

EWT was accurately estimated from the inversion of the PROSPECT model (Fig. 3). The simulation for EWT together with the one for DM did not predict FMC accurately ($r^2 = 0.33$), but the use of simulated DM from dry samples for

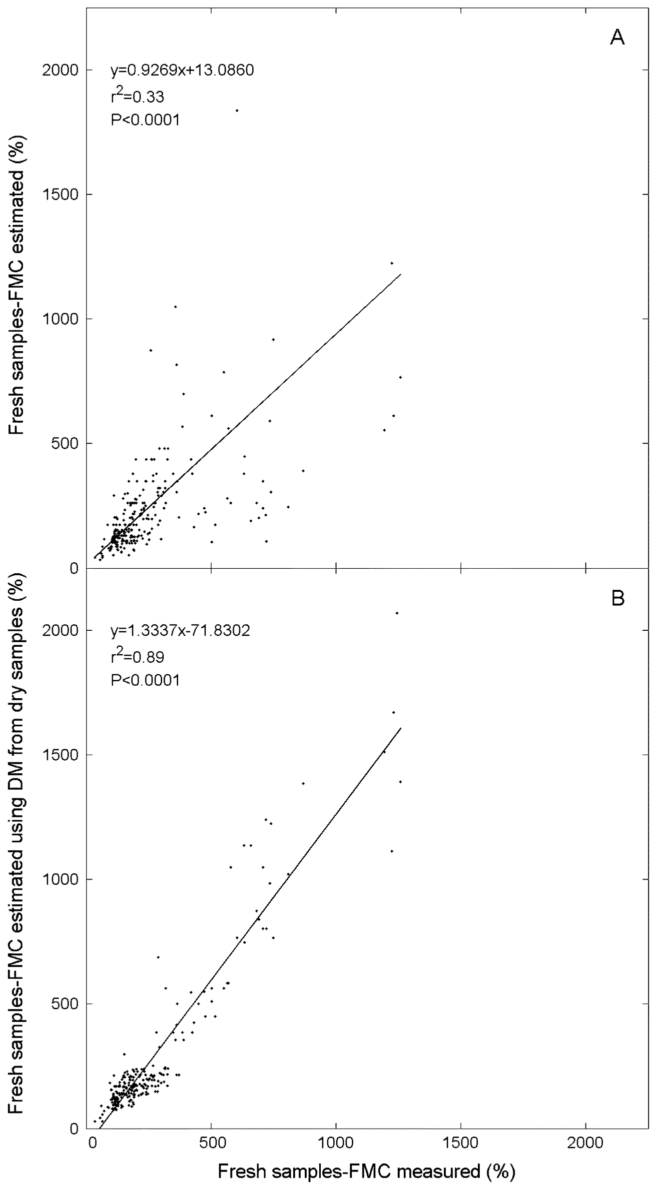

Fig. 4. FMC estimation at leaf level using fresh samples of LOPEX data ($n = 245$). Two approaches, one using simulated EWT and DM from (A) the PROSPECT model and (B) the other using DM of dry samples for each species instead of the simulated DM of fresh samples.

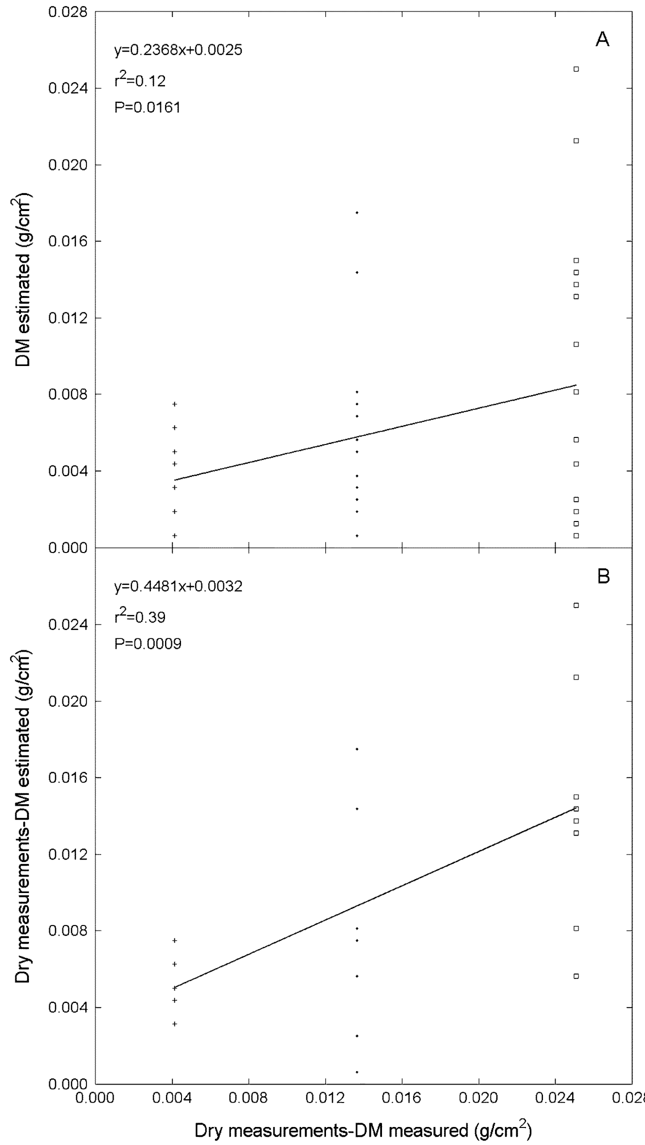

Fig. 5. DM estimation at canopy level for the laboratory experiment, using (A) all measurements ($n = 49$) and (B) only those with $\mathrm{FMC} < 75\%$ ($n = 25$). Each species represented with a different symbol: (+) gall oak, (□) rosemary, and (●) rock rose.

each species improved greatly the results for the estimation of FMC ($r^2 = 0.89$) (Fig. 4).

B. Analysis at Canopy Level of FMC

The inversion of the PROSPECT–Lillesaeter model using the laboratory measurements to estimate DM (Fig. 5) failed when considering all samples ($r^2 = 0.12$). The result improved when taking into account measurements with FMC $< 75\%$ ($r^2 = 0.39$). The EWT prediction was more accurate than that of DM ($r^2 = 0.75$) (Fig. 6), but, as expected, not as good as the EWT prediction at the leaf level. The slope of the equations for the prediction of DM and EWT did not follow a 1 : 1 relationship. The steps in Fig. 5, with equal DM value measured, were due the same measured DM in each of the three samples, changing EWT as we were drying them in the oven.

The estimation of FMC using the simulation of EWT and DM ($r^2 = 0.62$) improved after calculating the average DM estimated for each species ($r^2 = 0.81$) and again the equation provided a 1 : 1 relationship (Fig. 7). Note also that all species were quite mingled, with rosemary having noisier results.

IV. Discussion

The inversion of the PROSPECT model for the estimation of DM for fresh and dry samples showed consistent results with those of Jacquemoud *et al.* [14]. Jacquemond *et al.* [27] obtained a higher correlation for DM ($r^2 = 0.65$), but their result was based on average values of every 5 leaves ($n = 63$) whereas our result was not ($n = 245$). DM of fresh samples could not be appropriately estimated probably because of the higher specific absorption coefficient of water [27], which masks the effect of DM on the spectral response. According to the analysis of correlation for each wavelength, DM had little effect on reflectance or

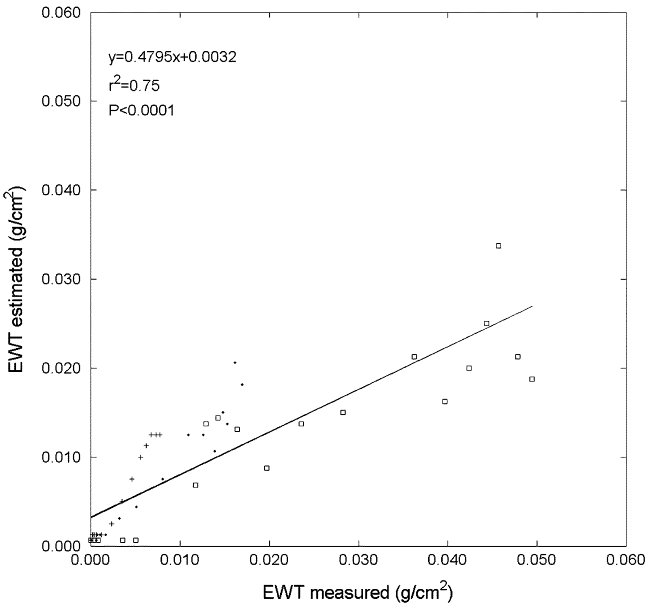

Fig. 6. EWT estimation at canopy level for the laboratory experiment ($n = 49$). Each species represented with a different symbol: (+) gall oak, (□) rosemary, and (●) rock rose.

transmittance of fresh LOPEX leaves [Fig. 1(A) and (B)]; therefore, neither PROSPECT nor probably could any other model provide a good estimation of DM for fresh leaves.

In order to solve this problem in the DM estimation, this paper demonstrated that DM of fresh samples can be obtained using estimated DM values from dry samples. This approach was possible because DM varies mainly between species (Table I), whereas the origin of each leaf or the degree of moisture within each species is less significant. Shipley and Vu [19] also established that DM is essentially species dependent, however, accounting for even more variance (94.8%) than was seen in our case (79.4%), on a dataset of 28 trees, shrub, and grass species. In addition, DM had a high impact mainly on transmittance of dry LOPEX leaves, especially in the SWIR [Fig. 1(D)], where specific absorption coefficient of DM is higher [27].

EWT was clearly related to the spectral response and rendered a similar fit to the one found in the literature [14]. EWT is one of the components used to estimate FMC, but Ceccato *et al.* [28] showed that reflectance was insensitive in some cases to FMC variations: samples having similar reflectance could have different FMC values and samples with different reflectance could have the same FMC. This could occur because spectral response is independent of DM values for fresh samples. However, we demonstrated that FMC could be estimated considering DM approximated from dry samples. The PROSPECT version was updated using LOPEX, but according to Fig. 1 other models could estimate DM from dry samples, whereas they also would be unlikely to successfully estimate DM from fresh samples.

Although similar trends were encountered, the analysis on a canopy level was less successful. DM estimation improved when considering only dry samples ($\mathrm{FMC} < 75\%$). The inversion of the PROSPECT–Lillesaeter model underestimated both DM ($\mathrm{slope} = 0.45$) and EWT ($\mathrm{slope} = 0.48$). This may be partially attributed to the kind of canopy model applied. This model was specifically designed for infinitive reflectance of stacked leaves. Infinitive reflectance was acquired when $\mathrm{LAI} > 4$ [18] while in our case LAI was around 3, so some residual effect from the background could remain. We also tested PROSPECT-SAILH model, which accounts for the influence of the background, but it provided worse results (not shown in this paper) probably because we were working with stacked leaves instead of a real canopy. The underestimation affected similarly both EWT and DM (estimated from dry samples) therefore the FMC was obtained following a 1 : 1 relationship. Noisier results for rosemary could be due to the needle-shaped leaves that made it difficult to obtain accurate leaf measurements.

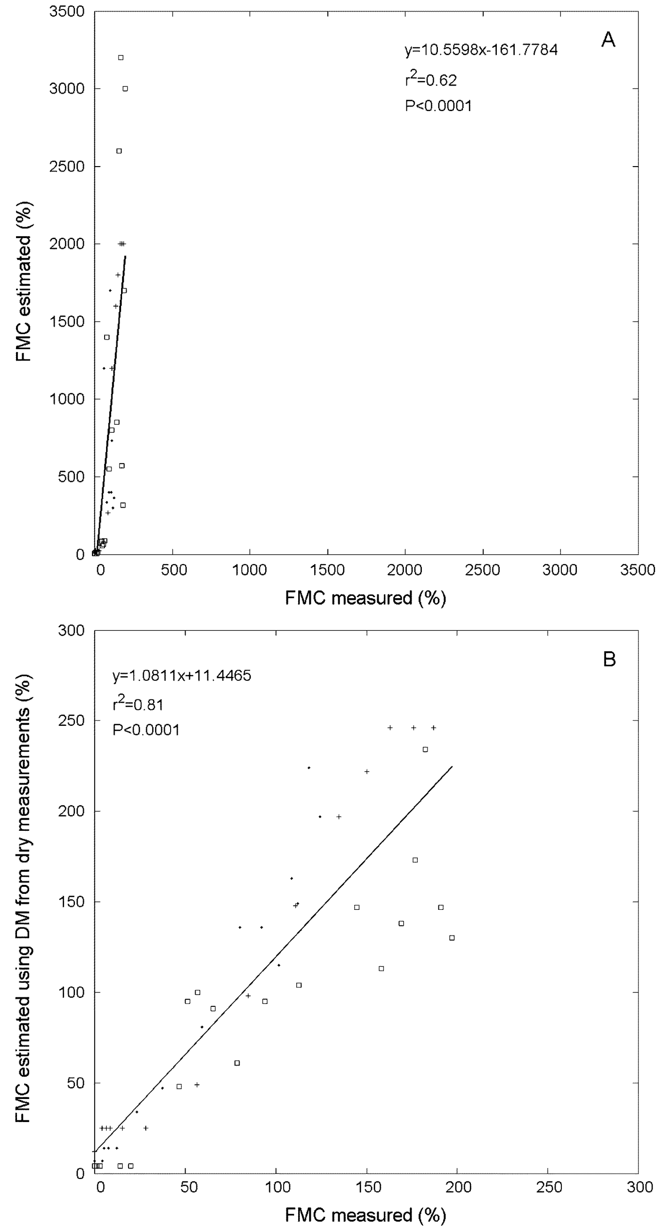

Fig. 7. FMC estimation at canopy level for the laboratory experiment ($n = 49$). Two approaches, one using simulated EWT and DM from (A) the PROSPECT–Lillesaeter model and (B) the other using DM of measurements with $\mathrm{FMC} < 75\%$. Each species represented with a different symbol: (+) gall oak, (□) rosemary, and (●) rock rose.

Previous research focused on estimating FMC applying a different empirical model for each group of species, namely grass versus shrubs [5], [7]. Chuvieco *et al.* [17], have already shown how multitemporal variations of NDVI and surface temperature (ST) helped to fit a single model for different species. This could be the case according to our research because differences in DM between species were taken into account when using multitemporal NDVI and ST series. A physically based model, such as the one applied here, avoids having to calibrate and could be applicable over a wide variety of environments, but it still needs to be tested on real canopies.

To date FMC estimation has mainly been attempted via empirical models. We demonstrated that the inversion of radiative transfer models could be used to estimate FMC, through separate predictions of EWT and DM, and could be applied on a wide variety of species. The spectral response for DM estimation was masked in fresh samples but not in dry samples. FMC is critical mainly for fire danger assessment in climates with a seasonal drought period. DM levels could be estimated from the driest time of the season in order to obtain a more accurate measurement of FMC. DM is assumed to be constant throughout the year, although an overall decrease in DM is expected during the drought period [29] because of decreased productivity, found to be -24% in their study. However, according to the analysis of variance (Table I), DM depended much more on the type of species than on the degree of moisture. Another option could use EWT in fire danger assessments, since it is easier to estimate from remote sensing than FMC. Further research will consist on testing this approach on real canopies as observed from airborne or satellite imagery, where the influence of soil and plant species mixing complicate the estimation of EWT and DM [15].

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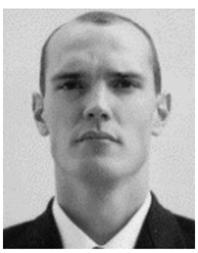
David Riaño received the Ph.D. degree in environmental sciences from the University of Alcalá, Madrid, Spain, in 2002.

He is currently a Researcher in the Department of Geography at the University of Alcalá and collaborates with the Center for Spatial Technologies and Remote Sensing. His research interests are fuel type mapping and vegetation moisture content.



Patrick Vaughan is currently pursuing the Ph.D. degree at the University of Alcalá, Madrid, Spain.

He is with the National Institute of Aerospatial Technology (INTA), Torrejón de Ardoz, Spain. His research interests are field spectroradiometry and vegetation moisture content.

Emilio Chuvieco received the Ph.D. degree in geography from the University Complutense, Madrid, Spain, in 1985.

He is currently a Professor in the Department of Geography, University of Alcalá, Madrid, where he coordinates the Ph.D. program on cartography, GIS, and remote sensing. His research interests are vegetation moisture content, fuel type mapping, burned area mapping, fire danger, and human factors of fire risk.

Pablo J. Zarco-Tejada received the Agricultural Engineering degree from the University of Córdoba, Córdoba, Spain, the M.Sc. degree in remote sensing from the University of Dundee, Dundee, U.K., and the Ph.D. degree in earth and space science at York University, Toronto, ON, Canada.

He is currently with the Institute for Sustainable Agriculture, Spanish Council for Scientific Research (CSIC), Córdoba, where he works with airborne CASI and AVIRIS hyperspectral data to estimate leaf biochemical and canopy biophysical variables through leaf and canopy modeling, and the effects of chlorophyll fluorescence on leaf apparent reflectance through radiative transfer simulation. He was a Postdoctoral Researcher and Lecturer in remote sensing at the University of California, Davis, working with multi- and hyperspectral airborne and satellite (Hyperion) data for vegetation water content estimation using leaf and canopy models.

Susan L. Ustin (M'90–SM'04) received the B.S. and M.S. degrees in biology from the California State University, Hayward, and the Ph.D. degree in botany in the area of plant physiological ecology from the University of California, Davis (UC-Davis).

She is currently a Professor in the Department of Land, Air, and Water Resources, UC-Davis. Since 1983, her research has focused on the use of remote sensing instruments to measure ecological properties and processes. In particular, she has been active in the development of imaging spectrometry from airborne and spaceborne platforms for measuring ecosystem properties. Her research has focused on developing and testing methods for retrieving environmental information from remote sensing imagery at spatial scales from microscopic to regional and encompasses both theoretical and applied research. She has studied many different ecological communities and farmlands in the United States and abroad. She is Director of the UC-Davis California Space Institute Center of Excellence and the Center for Spatial Technologies and Remote Sensing (CSTARS), and is Director of the Department of Energy's Western Center for Global Environmental Change (WESTGEC), Davis.