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Review

A global review of remote sensing of live fuel moisture content for fire danger assessment: Moving towards operational products

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ABSTRACT

One of the primary variables affecting ignition and spread of wildfire is fuel moisture content (FMC). Live FMC (LFMC) is responsive to long term climate and plant adaptations to drought, requiring remote sensing for monitoring of spatial and temporal variations in LFMC. Liquid water has strong absorption features in the near- and shortwave-infrared spectral regions, which provide a physical basis for direct estimation of LFMC. Complexity introduced by biophysical and biochemical properties at leaf and canopy scales presents theoretical and methodological problems that must be addressed before remote sensing can be used for operational monitoring of LFMC. The objective of this paper is to review the use of remotely sensed data for estimating LFMC, with particular concern towards the operational use of LFMC products for fire risk assessment. Relationships between LFMC and fire behavior have been found in fuel ignition experiments and at landscape scales, but the complexity of fire interactions with fuel structure has prevented linking LFMC to fire behavior at intermediate scales. Changes in LFMC have both direct (liquid water absorption) and indirect (pigment and structural changes) impacts on spectral reflectance. The literature is dominated by studies that have used statistical (empirical) and physical model-based methods applied to coarse resolution data covering the visible, near infrared, and/or shortwave infrared regions of the spectrum. Empirical relationships often have the drawback of being site-specific, while the selection and parameterization of physically-based algorithms are far more complex. Challenges remain in quantifying error of remote sensing-based LFMC estimations and linking LFMC to fire behavior and risk. The review concludes with a list of priority areas where advancement is needed to transition remote sensing of LFMC to operational use.

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1. Introduction

Fuel moisture content (FMC), the mass of water contained within vegetation in relation to the dry mass, is a critical variable affecting fire interactions with fuel. FMC is one of the primary variables in many fire behavior prediction models and fire danger indices, as it affects ignition, combustion, the amount of available fuel, fire severity and spread, and smoke generation and composition (Anderson & Anderson, 2010; Deeming et al., 1978; Finney, 1998; McArthur, 1967; Nelson, 2001; Plucinski et al., 2010; Viegas et al., 1992). FMC is usually separated into dead (DFMC) and live (LFMC) components. In many fire risk models, DFMC is empirically determined from weather variables, diameter of the material and biochemical compositions (Viney, 1991).

LFMC is much more difficult to estimate from meteorological indices than DFMC, because living plants have a variety of drought adaptation strategies (Viegas et al., 2001) and can draw upon moisture stored in the soil. The Keetch-Byram Drought Index (KBDI, (Keetch & Byram, 1968)) has been indirectly correlated with LFMC for some species (Dimitrakopoulos & Bemmerzouk, 2003; Xanthopoulos et al., 2006), while other species appear to be driven more by medium-term meteorological conditions or phenology (Castro et al., 2006; Pellizzaro et al., 2007; Zylstra, 2011a). Even though DFMC across a landscape is a determinant of landscape connectivity and therefore the potential area burnt (Caccamo et al., 2012a), the correlation of intense fire behavior with more persistent indicators such as deep soil dryness and/or extended heatwave conditions suggests that the moisture conditions of live fuels are also important determinants of fire behavior. For instance, the Black Saturday bushfires of February 2009 in Victoria, Australia, during which 173 people died and more than 3500 houses were destroyed, occurred after weeks of extreme record-breaking high temperatures, which dried many plants to critically low levels (Gellie et al., 2010). Drought had a major influence on the incidence of large bushfires (≥1000 ha) in the Sydney Basin Bioregion, New South Wales, Australia, through drying of fuels over extended areas (Bradstock et al., 2009). The 2003 Sant Llorenç Fire in Catalonia, Spain, also occurred following a period where very hot, dry Saharan air produced critical moisture stress in plants (Oliveras et al., 2009). Very low LFMC and dry, warm, Santa Ana winds contributed to large bushfire events in southern California in 2003 and 2007 (Keeley, 2004; Keeley et al., 2009).

In grasses, live and dead fuel loads are variable through time as senescence converts live fuel to dead fuel. The proportion of herbaceous fuel that is dead is important in determining the probability of ignition and rate of spread (ROS) of wildfires (Cheney et al., 1998), which has led to the use of vegetation indices for estimation of dead versus live fuels proportion to compute fire danger potential (Burgan et al., 1998; Newnham et al., 2011).

Obtaining spatially comprehensive and temporally frequent estimates specifically for LFMC is more problematic. Field sampling and gravimetric methods (Lawson & Hawkes, 1989) are locally accurate but very costly. Furthermore, generalization of these measurements to landscape, regional, or global scales is not feasible from field sampling. Remotely sensed (RS) data provide the opportunity to estimate LFMC over large areas at fine spatial and temporal resolutions, but as illustrated in this review, these data require calibration and validation. The initial hypothesis behind satellite-based estimation of LFMC is that the impact of LFMC variation on the RS signal is strong enough to be discriminated from other factors affecting spectral variation such as the atmosphere, soil background, solar and sensor geometry, and other plant characteristics. Several studies have been published in recent years to test this hypothesis (Bowyer & Danson, 2004; Ceccato et al., 2001; Gillon et al., 2004; Riaño et al., 2005) and multiple methods have been developed to estimate LFMC from both coarse and fine spatial resolution remote sensors (e.g. Chuvieco et al., 2002; Peterson et al., 2008; Wang et al., 2013; Yebra et al., 2008b). However, despite the success of these methods few of the resulting products have been operationally integrated into wildfire danger systems to date.

The objective of this paper is to review the use of RS data for estimating LFMC to assess its potential, with the anticipation that these RS-based products will soon become useful for operational use. To address this objective we will cover the following aspects: (i) importance of estimating LFMC in the context of fire risk assessment (Section 2); (ii) methods of measuring vegetation water content and their relationships with LFMC (Section 3); (iii) field data collection challenges and recommendations (Section 4); (iv) models that have been developed to derive LFMC from RS data as well as a brief review of the physical bases for a RS based estimation of LFMC (Section 5); (v) challenges and developments in satellite-based estimation of this variable (Section 6); (vi) obstacles for the operational use of LFMC models and products (Section 7); and (vii) priorities for research and applications within this field (Section 8).

2. The importance of LFMC for fire risk assessment

The effects of LFMC on fire behavior are complex and not always easy to identify empirically. Elevation of fuel temperature to the combustion point requires loss of water through evaporation; thus, higher LFMC should increase the time to ignition and decrease the probability of ignition. LFMC has therefore been demonstrated to be a primary determinant of time to ignition across multiple species at low to moderate temperatures (Xanthopoulos & Wakimoto, 1993), exhibiting a geometrically decreasing effect as temperatures are raised (Zylstra, 2011a) until the effect is negligible at temperatures corresponding with the hottest parts of a flame (Fletcher et al., 2007). LFMC has also been shown to correlate negatively with flame length from burning leaves (Zylstra, 2011a).

The way in which these factors affect fire behavior and risk is complex and the subject of debate. Plucinski et al. (2010) found that in laboratory recreations of shrub fires, the most important factors for spread initiation were LFMC and the presence of litter, and that shrub density has a greater influence at lower moisture contents (see figure 3 Plucinski et al. (2010)). Similar effects on fire propagation in shrub fuels have also been identified in field conditions (Davies et al., 2009; Weise et al., 2005).

While these studies demonstrate the importance of LFMC in determining the incidence and scale of fires, specific influences on some areas of fire behavior are less obvious. In a continuous fuel bed, ROS can be expected to decrease as FMC increases, since fire velocity is equal to the distance to ignition divided by time to ignition. This is widely accepted for DFMC in a range of fire behavior models (e.g. Burrows, 1999; Gould et al., 2007; McArthur, 1962; Rothermel, 1972), and Viegas et al. (in press) demonstrated that ROS in a mixed bed of live and dead fuels was explained by the composite FMC derived from both live and dead values. The relationship is far less obvious in a discontinuous fuel bed however, and in their review of historical heathland and crown fire experiments Alexander and Cruz (2012) found an influence in laboratory experiments but not in the field, proposing that the discrepancy was potentially due to the larger heat fluxes present in field conditions. In this context, Zylstra (2011a) noted that fire behaviors in discontinuous fuels are not directly determined by causal factors, but are rather emergent properties of the interactions between the flammability of plant parts, forest geometry and exogenous factors, and are therefore subject to numerous complex behaviors and feedbacks that unless specifically accounted for in experimental process will confound any clear results. This model also suggests that greater heat fluxes do not override the influence of LFMC on leaf ignitability, but rather have the effect of igniting leaves at a greater distance ahead of the burning fuels. This implies that the laboratory experiments identified an influence of LFMC because they were able to control for a wider range of variables relevant to the scale of the fuel complexes examined.

Although the immediate influence of LFMC on fire behavior may be difficult to capture empirically, the overall effect becomes apparent as an emergent property when the relationship is studied on a landscape scale. Multiple studies using fire histories from Mediterranean ecosystems have demonstrated relationships between LFMC and actual fire occurrence and size. Schoenberg et al. (2003) examined monthly trends in chaparral LFMC in Los Angeles County, California, USA, and found that burned area increased when LFMC dropped below 90%. Dennison et al. (2008) investigated relationships between chamise (*Adenostoma fasciculatum*) LFMC and fire size and occurrence in the Santa Monica Mountains of California. They found that while small fires occurred across a wide range of LFMC values (59–139%), large fires (>10 km^2) only occurred when chamise LFMC was below 77%. Dennison and Moritz (2009) expanded this analysis to Los Angeles County, California, and found similar relationships between the occurrence of large fires and chamise LFMC, with a LFMC threshold near 79%.

Chuvieco et al. (2009) also showed that lower LFMC increases fire occurrence for shrublands and grasslands in the Cabañeros National Park located in central Spain. Moisture variations in grasslands were found to be good predictors of the number of fires and total burned surface, while both the total burned area and the occurrence of large fires were more sensitive to moisture variations of two shrubs (*Cistus ladanifer* L. and *Rosmarinus officinalis* L.). Jurdao et al. (2012) related seven years of MODIS thermal anomalies (MOD14, (Giglio et al., 2003)) with LFMC calculated from Advanced Very High Resolution Radiometer (AVHRR) data using an empirical algorithm developed by Garcia et al. (2008). They found significant differences between fire and non-fire pixels and several spatial and temporal variables derived from LFMC.

Outside Mediterranean ecosystems, there have been few comparisons between LFMC and fire occurrence. Maki et al. (2004) used burning areas obtained from AVHRR to confirm the relationships between a vegetation dryness index (VDI) and ignited pixels and fire behavior. A hypothetical trapezoidal shape was first defined by the normalized difference vegetation index and normalized difference water index of the research region bounded by four vertexes of their maximum and minimum values using SPOT/VEGETATION data. To estimate water status per fractional vegetation cover, the VDI was calculated as 1 subtracted by the ratio between a point's distance to the trapezoidal left side and distance to the right side. The VDI values of fire-spread pixels were higher than those of the non-fire-spread pixels and the fire front length was strongly related to VDI. Drought conditions have been found to be closely related to the area burned by unplanned fire in the Sydney sandstone area (Bradstock et al., 2009), and Caccamo et al. (2011) demonstrated that this was closely tied to greater landscape connectivity resulting from reductions in LFMC.

Overall then, there is strong empirical evidence demonstrating the effect of LFMC on fire occurrence and the extent of its impact, and laboratory evidence demonstrating the direct relationship to fire behavior. Field evidence for this connection is inconclusive; however there are physical arguments that explain why the connection is not always clear, and the observed effect of LFMC on fire size demonstrates that such relationships must exist as emergent properties even if not yet captured experimentally.

3. Measures of vegetation water content and relationships with LFMC

LFMC is a ratio of the mass of water contained in a live plant to the total dry mass of the plant. Changes in LFMC are driven by both changes in the moisture status of the leaves and seasonal changes in dry matter, which represents the amount of available fuel to be burned. Field sampled LFMC is calculated as:

$$LFMC = \frac{m_f - m_d}{m_d} \tag{1}$$

where m_f is the mass of the "fresh" collected sample and m_d is the dry mass of the same sample.

When measuring moisture content in RS-based studies, the most commonly used metric is the amount of leaf water divided by its area (A), which is called the equivalent water thickness (EWT, g cm^{-2}):

$$EWT = \frac{\left(m_f - m_d\right)}{A}. \tag{2}$$

EWT is more relevant to RS studies as the water absorption of incoming radiation is directly related to the depth of the water layer, particularly in the near infrared (NIR: 700 to 1400 nm) and shortwave infrared (SWIR: 1400 to 2500 nm) spectral bands.

EWT and FMC are linked through the dry matter content (DMC, g cm^{-2}), which is the inverse of the specific leaf area (SLA, cm^2 g^{-1}), a more common term in plant physiology and functional ecology (Garnier & Navas, 2012). DMC describes the areal expression of cellulose, lignin and other components of plants that remain after drying. DMC is defined as:

$$DMC = \frac{m_d}{A}. \tag{3}$$

DMC can be used to normalize the water mass per area and calculate FMC following:

$$LFMC = \left(\frac{\frac{\left(m_f - m_d\right)}{A}}{\frac{m_d}{A}}\right) = \frac{EWT}{DMC}. \tag{4}$$

Eqs. (1) to (4) also apply to the calculation of DFMC.

Since only EWT is directly related to radiation absorption by water, the estimation of LFMC partially relies on the accuracy of DMC estimates (Riaño et al., 2005). DMC does not have strong specific absorption features (Fourty & Baret, 1997), and therefore the estimation of LFMC from RS data is more challenging than estimation of EWT.

LFMC calculated in Eqs. (1) and (4) is independent of the leaf area and the amount of leaves that constitute the canopy or leaf area index (LAI). However, this last parameter is extremely helpful when calculating the total canopy water content in the leaves per unit ground area (CWC, g m^{-2}) which is commonly computed by multiplying the mean leaf EWT of a sample area by the LAI:

$$CWC = EWT \times LAI. \quad (5)$$

Consequently, CWC allows scaling leaf water content to the canopy level and influences the amount of reflected radiation measured by remote sensing. CWC has been related to LFMC (Zarco-Tejada et al., 2003) and may be correlated with LFMC if species happen to have similar DMC (Chuvieco et al., 2003; Yebra et al., 2008b).

Senescence in grasses results in conversion of live fuel to dead fuel over time. LFMC may not be separable from DFMC in partially cured grasses, and estimated LFMC may represent an aggregate of both measures. In the sections that follow, grassland LFMC is considered as the average moisture content of both live and dead fuel components, and the degree of curing is not explicitly accounted for.

4. Field measurements of LFMC

Field measurements of LFMC are essential for calibration and validation of satellite-based methods for estimating LFMC. Field measurement of LFMC is straightforward requiring destructive sampling of a representative sample of leaf material which is then weighed fresh, oven dried, and reweighed to determine dry weight. However the sampling design, in terms of the number of samples and their location, must take into account the variability in LFMC that may occur within individual plants in both horizontal and vertical directions, and the variability between plants within the sampled area. Sampling leaves from broadleaved trees may be simple, but sampling leaves in some shrub species, where there is a mix of woody and leafy material, may be more complex.

The key difficulty in making LFMC field measurements is ensuring that they are spatially comparable to the RS data and this problem has often limited scientists' ability to develop methods for monitoring LFMC from space. The primary limitation is the spatial scale of sampling. RS data suitable for monitoring LFMC are typically collected at spatial scales ranging from 0.1 to 100 ha, while LFMC is typically sampled at smaller scales ranging from 0.01 to 0.1 ha. Field measurement of LFMC for comparison with satellite-based measurements requires:

(i) Site metadata, including sampling locations and dates, should always be recorded. The coordinates of the center of the sampling site is often sufficient, but a polygon around the perimeter of the sampling site is much more useful. As much as possible, the same site should be sampled to create a long-term record of LFMC for that site. A change of a few meters that results in a different slope or aspect being sampled could make time series comparison much more difficult.

(ii) The area surrounding LFMC sampling sites should be as homogeneous as possible in vegetation and topography over an area of 100 ha to make the comparison between LFMC and RS data feasible. In some regions, this might be impossible but sites selection should still be optimized.

(iii) Sites should ideally be dominated by one vegetation type, and mixed vegetation sites should be avoided. For each site, all dominant species presented should be sampled and their fractional coverage should be recorded.

Databases have been created to collect field-sampled LFMC data (e.g. the U.S. National Fuel Moisture Database (http://www.wfas.net/nfmd/public/index.php, last accessed February 2013) and the LFMC database developed from 1996 to 2010 by the University of Alcalá (Spain) (Chuvieco et al., 2011)). However a global network to routinely measure LFMC following a common sampling methodology or protocol at the appropriate spatial and temporal resolutions has not been established. This observational limitation makes it difficult to obtain LFMC at a sufficient number of locations within a short time interval to calibrate and validate satellite data products. A recent development in the application of terrestrial laser scanning to measure vegetation EWT may in future provide a rapid non-destructive approach to obtain LFMC in three dimensional space over spatial ranges of 10–100 m based on dual-channel laser scanner measurements within a sampling plot (Gaulton et al., 2013).

A common sampling protocol should address issues related to (i) plot size, (ii) the best time to acquire the samples, (iii) what to do when precipitation occurs, (iv) how many samples per plot to take, (v) which kind of material to harvest (new and old leaves, combine leaves and shoots, include grassland roots, etc.), how much material and how many samples to take, (vi) information about the weighting procedure (if the samples were weighted on the field or in the lab and the weighing device accuracy), (vii) details about the drying process (drying device, drying time and temperature) and (viii) the material used to seal the samples for transportation to the lab, (see for e.g. Desbois et al. (1997) and Zahn and Henson (2011)). Further work is needed to understand spatial variability in LFMC across plant, local, and regional scales to better inform sampling strategy.

5. Estimation of LFMC from satellite data

Various methods have been developed to estimate LFMC from RS data, which may be broadly classified into statistical (empirical) (Caccamo et al., 2012b; Dennison et al., 2005; Garcia et al., 2008; Peterson et al., 2008) and physical model-based approaches (Colombo et al., 2008; Yebra & Chuvieco, 2009a; Yebra et al., 2008b; Zarco-Tejada et al., 2003). The type of sensor used to acquire RS data is an important consideration for either method. Table 1 summarizes some examples of application of RS data for LFMC estimation. Most of the studies in Table 1 are focused on high temporal resolution sensors with a few spectral bands, such as MODIS. Spectral vegetation indices (VI) are an efficient means of obtaining empirical information from multispectral sensors; however physical model-based methods also benefit from VI. Typically, hyperspectral sensors are used for physical model-based methods, since the numerous narrow spectral bands offer the possibility of novel VI.

The decision to use any combination of method, sensor and spectral information to estimate LFMC depends on the objectives of the research. Before going into detail we will briefly review the physical basis for a RS-based estimation of LFMC.

5.1. Physical basis for a RS-based estimation of LFMC

In the solar spectral domain, water has a direct effect on spectral reflectance through absorption of radiation within the NIR and SWIR spectral regions. Depending on tissue water content, reflectance is thus reduced to a varying extent within the water absorption features centered on 970, 1200, 1450, 1940, and 2500 nm (Knipling, 1970; Thomas et al., 1971; Tucker, 1980). RS methods which make use of these absorption features are considered direct estimation techniques. However, changes in leaf pigment concentrations and leaf internal structure co-vary with LFMC, and produce changes in visible and NIR reflectance that may be correlated with LFMC (Fig. 1). When plants are under water stress, depletion of chlorophyll may produce a decrease in reflectance in the visible bands, especially in the red end of the visible spectrum. When leaves wilt during

Table 1
Examples of studies using RS data to estimate LFMC. Methodologies, sensors, spectral and ancillary information used, and vegetation types are listed, along with the corresponding reference. In the case of physical model-based (RTM) methodologies the inverse method is indicated. LUT is look-up table, # sites is the number of sites used in the study, ST is the surface temperature, DOY is a function of the day of the year, LCT is the land cover type, TM is the reflectance in a Landsat Thematic Mapper-like broad waveband and Ccov is the canopy coverage.

Method	Sensor	Spectral information	Ancillary information	Vegetation type	Locations	# sites	Independent validation	Reference
Empirical	AVHRR	NDVI	ST, DOY, LCT	Mediterranean grasslands and shrublands	Spain	7	Yes	Chuvieco et al. (2004c)
Empirical	MODIS	NDWI, VARI	None	Chaparral	California, U.S.A.	3	No	Stow et al. (2005)
Empirical	MODIS	NDVI, NDWI	None	Chaparral and coastal shrubland	California, U.S.A.	12	No	Dennison et al. (2005)
Empirical	MODIS	B1, B2, B3, B4, B5, B6, B7, NDVI, SAVI, EVI, NDWI, NDII6, NDII7, NDGR, VARI	None	Chaparral	California, U.S.A.	4	Yes	Stow et al. (2006)
Empirical	MODIS AVIRIS	NDVI, EVI, VARI, VIg NDII6, NDII7, NDWI, WI, EWT	None	Chaparral	California, U.S.A.	14	No	Roberts et al. (2006)
RTM-Simulations Empirical	MODIS	B1, B2, B3, B4, B5, B6, B7	None	Pine stands and hard wood dominated areas	Georgia, U.S.A.	2	No	Hao and Qu (2007)
Empirical	MODIS	NDII6, NDWI, VARI Max–min scaled NDII6, NDWI, VARI	None	Chaparral	California, U.S.A.	11	Yes	Stow and Niphadkar (2007)
Empirical	MODIS	NDVI, EVI, VARI, VIgreen, NDII6, NDII7, NDWI	None	Chaparral and coastal sagescrub	California, U.S.A.	14	No	Peterson et al. (2008)
RTM-LUT Empirical	MODIS	NDVI, SAVI, EVI, GEMI, VARI, NDII6, NDWI, GVMI	LAI, DMC, LCT	Mediterranean Grasslands and shrublands	Cabañeros National Park, Spain	5	Yes	Yebra et al. (2008b)
Empirical	AVHRR	NDVI	ST, Function of day of year, LCT	Mediterranean Shrublands	Spain	7	Yes	Garcia et al. (2008)
RTM-LUT	MODIS	B1, B2, B3, B4, B6, B7	LAI, plant ecological information	Mediterranean Grasslands Mediterranean Shrublands	Spain	12	Yes	Yebra and Chuvieco (2009b)
RTM-LUT	MODIS	B1, B2, B3, B4, B6, B7, NDII6	None	Mediterranean Woodlands	Spain	5	Yes	Yebra and Chuvieco (2009a)
Empirical	MODIS	$VARI_{max-min}$ and $NDII6_{max-min}$	None	Shrubland, heathland and sclerophyll forest	South-eastern Australia	8	Yes	Caccamo et al. (2012b)
Empirical	AISA Eagle and Hawk sensors	Reflectance, first derivatives, MSI, WI, NDWI TM5/TM7, NDVI, NDII6	None	*Calluna vulgaris* and grassland	Central Pennine uplands, U.K.	10	No	Al-Moustafa et al. (2012)
Empirical	MODIS	NDVI, NDWI, CWC	None	Gambel Oak Sagebrush	Utah, U.S.A.	10	No	Qi et al. (2012)
RTM Simulations		NDWI, NDII6, SWRI, RMSI, NDMI, NDTI, CAI, NDLI, NDNI, LCA, SINDRI, DMCI, ratio of water index and dry-matter index	None	*Quercus alba*, *Acer rubrum* and *Zea mays*	None	None	Yes	Wang et al. (2013)
Empirical RTM, LUT	MODIS	B1, B2, B3, B4, B5, B6, B7, NDII6	LAI, Ccov	Woodlands	Spain	19	Yes	Jurdao et al. (2013)

dehydration and senescence, many of the reflective interfaces of leaves are eliminated as internal air space is reduced and cell walls come together, which reduces NIR reflectance (Knipling, 1970).

Additionally, LFMC changes affect plant canopy temperature because water availability is a critical parameter in plant evapotranspiration. When the plant dries, transpiration and latent heat transport is reduced, which increases sensible heat (Kozlowski et al. 1991). As a result of this relation, the difference between air and canopy surface temperature (ST) should be clearly related to plant water content and to water stress (Boulet et al., 2007; Gonzalez-Dugo et al., 2012; Moran et al., 1994; Rahimzadeh-Bajgiran et al., 2012; Vidal et al., 1994).

Finally the microwave region has also been found to be sensitive to water content of plant and soil moisture. Changes in dielectric constant associated with the water content of biomass components (leaves, branches, and stems) impact the radar backscatter measurements and introduce larger variability when compared with dry biomass (Way et al., 1991). However the use of microwave images for retrieval of plant water content is more complex than with optical sensors, and presents different factors of potential confusion, such as vegetation biomass, height, topographic position or roughness (Beaudoin et al., 1995).

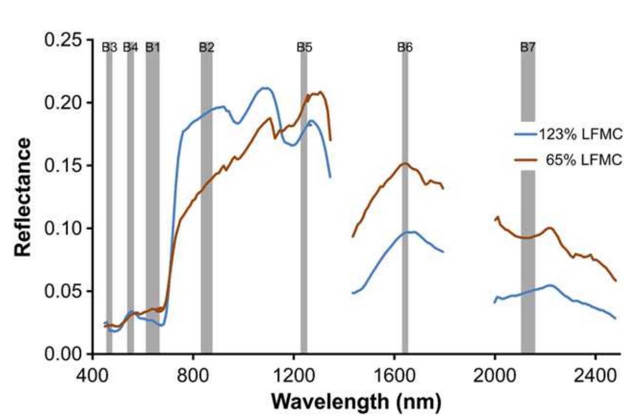

Fig. 1. Reflectance spectra for vegetation canopies with different LFMC values. Spectra were collected by the Airborne Visible Infrared Imaging Spectrometer (AVIRIS) over a plot dominated by *Adenostoma fasciculatum* in southern California, U.S.A. The approximate spectral extent of the first seven MODIS bands is also shown in gray.

5.2. Statistical versus physical model-based approaches

Empirical methods for LFMC estimation are commonly based on statistical fitting between field-measured LFMC and spectral measures based on reflectance data.

The alternatives to empirical approaches are those based on simulation models, which use physical models to estimate a parameter (water content in this case), based on a set of simulation scenarios. The estimation is commonly based on comparing the observed reflectances of every pixel to those simulated in a look-up table, assigning to each pixel the parameters of the most similar simulated spectrum. The concept of 'similarity' is commonly formalized in radiative transfer model (RTM) inversion approaches using a merit function, which implies minimizing the differences between the observed and modeled reflectance. Several merit functions have been formulated and used for RTM inversion (Table 2). The RS inputs for the inversion can be either spectral waveband indices or both.

Yebra et al. (2008b) compared the performance of statistical and physical approaches to derive LFMC of Mediterranean grassland and shrubland species from MODIS reflectance measurements. Both approaches provided good estimations of LFMC for both vegetation functional types. The physical approach based on simulated data was more complex to parameterize, but offered lower standard errors of estimation of LFMC of 29.5% and 12.6% for grasslands and shrublands versus 30.1% and 17.5% for the statistical approach. The physical approach also proved more robust when several calibration samples were selected, since the coefficients of the calibrated models did not significantly vary with the samples used and consequently were expected to have a greater generalization power. This hypothesis was tested by Yebra et al. (2008a) with ground measurements obtained at other areas dominated by grasslands in Spain and Australia. The results showed that both physical and statistical models offered similar accuracy levels when applied to grassland with analogous types of vegetation to the calibration site with an average RMSE of LFMC of 42% and 36% for statistical and physical model approaches respectively. Nevertheless, the physical model offered greater accuracy than the statistical model when the models were applied to grasslands with different characteristics to those of the calibration sites with an average RMSE of 50% and 15%, for the statistical and physical model, respectively.

5.3. Fine versus coarse spatial and spectral resolution input data

Coarse spatial resolution, globally available AVHRR or MODIS data are the most common choice for estimating LFMC from RS data, as they provide high enough temporal resolution for operational applications. The first studies were carried out in the 1980s and 1990s, when strong correlations between LFMC and multitemporal series of AVHRR data were found for herbaceous species using the Normalized Difference Vegetation Index (NDVI, Table 3) (Chladil & Nunez, 1995; Paltridge & Barber, 1988). Weaker relationships were reported for shrubs and trees, as chlorophyll absorption and NIR reflectance do not correlate as strongly for these vegetation types as for grasses (Yebra et al., 2008b). Improved empirical models have combined NDVI with surface temperature, a seasonal trend index (Chuvieco et al., 2004c) and meteorological data (Garcia et al., 2008).

Table 2
Merit functions formulated in the literature and used for RTM inversion. $\rho_{i,\mathrm{Obs}}$ and $\rho_{i,\mathrm{mod}}$ are the observed and modeled reflectivity in each band i respectively, n the number of bands considered in the comparison and v and w are the observed and modeled spectra respectively, both of them considered as an n-dimensional feature vector.

Function	Formulation	Reference
Absolute error	$AE = \sum_{i=1}^{n} \left[\left\lvert\rho_{i,Obs} - \rho_{i,\mathrm{mod}}\right\rvert\right]$	Koetz et al. (2005)
Square error	$SE = \sum_{i=1}^{n} \left(\rho_{i,Obs} - \rho_{i,\mathrm{mod}}\right)^2$	Zarco-Tejada et al. (2003)
Root mean square error	$RMSE_p = \sqrt{\frac{1}{n}\sum_{i=1}^{n} \left(\rho_{i,Obs} - \rho_{i,\mathrm{mod}}\right)^2}$	Combal et al. (2002b)
Relative root mean square error	$RMSE^{*}p = \sqrt{\frac{1}{n}\sum_{i=1}^{n} \left(\frac{\rho_{i,Obs} - \rho_{i,\mathrm{mod}}}{\rho_{i,Obs}}\right)^2}$	Weiss et al. (2000)
Spectral angle	$SA\left(\vec{v}, \vec{w}\right) = \cos^{-1}\left(\frac{\vec{v} \times \vec{w}}{\left\lVert\vec{v}\right\rVert \times \left\lVert\vec{w}\right\rVert}\right)$	Jurdao et al. (2013) and Yebra and Chuvieco (2009b)

Since the launch of Terra and Aqua satellites by NASA in 1999 and 2002, respectively, MODIS data have been much more commonly used to estimate LFMC (Caccamo et al., 2012b; Dennison et al., 2005; Peterson et al., 2008; Roberts et al., 2006; Stow & Niphadkar, 2007; Stow et al., 2005, 2006; Yebra & Chuvieco, 2009a,b; Yebra et al., 2008b), as this sensor offers a finer spatial and spectral resolution than AVHRR, along with additional bands in the NIR and SWIR regions (Fig. 1). While MODIS and AVHRR will eventually become unavailable, the new Visible Infrared Imaging Radiometer Suite (VIIRS) is expected to provide data continuity with better spatial resolution (Lee et al., 2006).

Medium-spatial-resolution sensors such as Landsat Thematic Mapper (TM) and Enhanced Thematic Mapper + (ETM+) sensors have also been used to estimate LFMC (Chuvieco et al., 2002; Yilmaz et al., 2008). Chuvieco et al. (2004b) examined the correlation coefficients computed between VI derived from AVHRR, SPOT-Vegetation, Landsat TM, and field-measured LFMC and found consistent trends among the three sensors showing similar correlation values in spite of being from different time periods and having different spatial resolutions. Even though correlations were slightly stronger for Landsat TM images, the combination of temporal resolution (every 16 days for Landsat data) and cloud cover may limit the use of this type of medium spatial resolution data for LFMC monitoring applications.

Active microwave images have been used to examine LFMC in cloudy areas, because these wavelengths are not interfered with by cloud cover. Leblon et al. (2002) compared radar image intensity values from European Remote Sensing satellite Synthetic Aperture Radar (ERS-1 SAR) imagery collected over boreal forest in 1994 to LFMC data. The authors reported a significant relationship between rates of change in LFMC and radar backscatter, which can be largely accounted for in the relationship between rate of change in the backscatter coefficient and rates of change in the LFMC, and therefore good correlations can be found in areas where other forest parameters are relatively stable in time.

Airborne hyperspectral data have proven useful for LFMC retrieval and validation against satellite data (Al-Moustafa et al., 2012; Cheng et al., 2008, 2011; Roberts et al., 2006). Roberts et al. (2006) found stronger correlations between spectral indices calculated from Airborne Visible Infrared Imaging Spectrometer (AVIRIS) data and LFMC than indices calculated from MODIS data. However, while airborne data may be acquired on demand, they are unlikely to have the temporal resolution required for LFMC monitoring.

Current plans for a space-borne imaging spectrometer mission, the Hyperspectral InfraRed Imager (HyspIRI), specify a 19 day repeat coverage for the imaging spectrometer instrument (http://hyspiri.jpl.nasa.gov/, last accessed February 2013), which is an insufficient temporal resolution for monitoring LFMC, but would provide useful data for the calibration and validation of LFMC estimated from higher temporal resolution sensors. Combinations of coarse and moderate spatial resolution sensors may provide complementary spatial information for operational LFMC monitoring.

High spatial resolution sensors, such as Quickbird, Ikonos, GeoEye-1, and WorldView-2, have not previously been used for LFMC analysis. The limited spectral range of these sensors (4–8 bands covering the visible and near infrared) excludes measurement of spectral regions containing liquid water absorption features, although simple VI based on visible and near infrared reflectance may have some value. Data from the planned WorldView-3 mission, which includes a 3.7 m spatial resolution SWIR band, may prove more useful for high resolution LFMC analysis.

Table 3
Spectral indices used to estimate LFMC including their shortened acronym, mathematical formulation and reference. ρ is reflectance and the subscripts refer to MODIS bands shown in Fig. 1, except in the case of Water Index, where the subscripts refer to wavelength in nm.

Index	Formulation	Reference
Normalized Difference Vegetation Index	$NDVI = \frac{\rho_2 - \rho_1}{\rho_2 + \rho_1}$	Rouse et al. (1974)
Soil Adjusted Vegetation Index	$SAVI = (1 + 0.5)\ (\rho_2 - \rho_1) / (\rho_2 + \rho_1 + 0.5)$	Huete (1988)
Enhanced Vegetation Index	$EVI = \frac{2.5 \times (\rho_2 - \rho_1)}{(\rho_2 + 6 \times \rho_1 - 7.5 \times \rho_3 + 1)}$	Huete et al. (2002)
Visible Atmospherically Resistant Index	$VARI = (\rho_4 - \rho_1) / (\rho_4 + \rho_1 - \rho_3)$	Gitelson et al. (2002)
Vegetation Index — Green (also Normalized Green Red Difference)	$VI_{green} = (\rho_4 - \rho_1) / (\rho_4 + \rho_1)$	Tucker (1979)
Normalized Difference Infrared Index (with band 6)	$NDII6 = (\rho_2 - \rho_6) / (\rho_2 + \rho_6)$	Hardisky et al. (1983)
Normalized Difference Infrared Index (with band 7)	$NDII7 = (\rho_2 - \rho_7) / (\rho_2 + \rho_7)$	
Normalized Difference Water Index	$NDWI = \frac{\rho_2 - \rho_5}{\rho_2 + \rho_5}$	Gao (1996)
Water Index	$WI = R_{900}/R_{970}$	Peñuelas et al. (1993, 1997)
Global Vegetation Moisture Index	$GVMI = \frac{(\rho_2 + 0.1) - (\rho_6 + 0.02)}{(\rho_2 + 0.1) + (\rho_6 + 0.02)}$	Ceccato et al. (2002a)

5.4. Input data used to estimate LFMC

Atmospheric correction of satellite radiance measurements to retrieve apparent surface reflectance reduces the effects of variation in atmospheric conditions and solar irradiance. However, effects of different sensor view angles and differences in slope, aspect, and soil background reflectance are readily apparent in RS data. Removing such factors in spectral data means that any changes observed in the spectra are more likely to be related to leaf biochemical composition, leaf structure, or water content. VI are combinations of reflectance measured at two or more wavelengths, which tend to suppress these background effects and enhance spectral differences. VI can be directly or indirectly related to LFMC depending on the wavelengths used (Fig. 1). Liquid water absorbs radiation strongly in the SWIR, so indices that include reflectance in that region such as the Normalized Difference Infrared Index (NDII) (Table 3) are directly related to LFMC and have shown significant correlations with LFMC for grasslands, shrublands and woodlands (Chuvieco et al., 2002, 2004b; Roberts et al., 2006; Yebra et al., 2008b). MODIS band 5, centered on 1240 nm, also captures liquid water absorption. The Normalized Difference Water Index (NDWI) (Table 3) has been correlated with LFMC in southern California chaparral (Dennison et al., 2005; Roberts et al., 2006). Indices using only visible and NIR wavelengths with minimal water absorption, such as NDVI (Table 3), are indirectly related to LFMC. Visible-NIR indices are sensitive to both changes in pigment concentrations and changes in LAI that may correspond with changing LFMC. Multiple studies have found strong empirical relationships between the Visible Atmospherically Resistant Index (VARI, Table 3) and chaparral LFMC (Peterson et al., 2008; Roberts et al., 2006; Stow et al., 2005, 2006), as well as fire-prone vegetation types (shrubland, heathland and sclerophyll forest) in south-eastern-Australia (Caccamo et al., 2012b). NDVI and other visible-NIR indices are reliable indicators of vegetation phenology, and measures of phenological changes may lead to useful empirical relationships with LFMC (Hardy & Burgan, 1999).

The first derivative of canopy reflectance has been shown to be insensitive to variations caused by changes in illumination intensity, which may be related to variations in sun angle, cloud cover, atmospheric attenuation or topography (Blackburn, 2007; Imanishi et al., 2004). Another advantage of derivative analysis is that it can be used to determine the location of key spectral features such as the red edge, and chlorophyll absorption and, most importantly here, water absorption peaks in the near- and shortwave infrared. Al-Moustafa et al. (2012) successfully used airborne hyperspectral imagery to estimate LFMC in a *Calluna vulgaris*-dominated semi-natural upland area in the United Kingdom, but found that a broad waveband spectral index provided a very similar correlation with LFMC compared to that derived using first derivatives at selected wavelengths between 400 and 2500 nm derived from the hyperspectral data.

More complex measures based on full range reflectance spectra have also successfully been used to estimate LFMC. Roberts et al. (2006) found correlations between chaparral LFMC and both green vegetation and non-photosynthetic vegetation fractions calculated from AVIRIS and MODIS data using a spectral mixture model. Finally, several authors have used thermal infrared (TIR) data to estimate plant water content, mainly for crops (Gonzalez-Dugo et al., 2012; Jackson et al., 1981; Moran et al., 1994). Forest and shrub canopies are more complex, but relationships between the differences in air and surface temperature and LFMC have been also found (Chuvieco et al., 2004c). TIR radiation can be used alone or in combination with greenness vegetation indices such NDVI. The combined use of TIR and VI has shown statistically stronger relationships with LFMC than either of the two variables alone (Chuvieco et al., 2004c) because the differences in air and surface temperature are closely related to the density of vegetation coverage.

A breakthrough in TIR analyses was made using a synthesis of polar-orbiting and geostationary satellite RS data (Anderson et al., 2007, 2011; Kustas & Anderson, 2009). Geostationary RS data are spatially coarser than MODIS or AVHRR data, but geostationary sensors acquire a daily profile of land surface temperature, so that daily evapotranspiration can be more accurately estimated. Evapotranspiration estimates may reveal coarse scale drought stress, but plant physiological adaptations to drought stress (and thus LFMC) vary by vegetation type.

6. Challenges in estimating FMC from satellite data

The main challenges for estimating LFMC from satellite data fall into two categories: theoretical and methodological. The former challenges are common to all methods and are mainly derived from the strength of the theoretical link between LFMC variations, the detected signal and other factors affecting spectral variation and data quality. The latter challenges are those derived from the specific method or approach used to link spectral information to LFMC.

6.1. Theoretical challenges

6.1.1. Decoupling the impact of EWT from DMC on reflectance

The first theoretical challenge is related to the complexity of decoupling the impact of water from other factors affecting reflectance, temperature, or backscatter. For instance, at the leaf level, estimation of LFMC from NIR and SWIR data requires discriminating the contribution of DMC from EWT. Sensitivity analyses with RTM have proved that variations in reflectance when plants are drying are mainly due to both EWT and DMC (Ceccato, 2001; Danson & Bowyer, 2004). Riaño et al. (2005) showed that DMC of fresh samples could not be appropriately estimated from RTM because (i) the higher specific absorption coefficient of water over most of the solar-reflected spectrum (Fig. 2) and (ii) EWT is usually greater than DMC. However, where changes in leaf water content occur over a short time period and there is little change in DMC, we can expect strong relationships between leaf LFMC and spectral reflectance (Bowyer & Danson, 2004). Trombetti et al. (2008) inverted the PROSPECT-SAILH model optimized with artificial neural networks to determine CWC over the continental United States with MODIS data and validated their approach using CWC estimations obtained from AVIRIS airborne hyperspectral data. MODIS-CWC estimates gave consistent results throughout the continental USA but the algorithm does not retrieve DMC and thus does not directly estimate LFMC.

A few studies have attempted to measure canopy DMC with RS data. Accurate DMC retrieval would allow conversion of CWC to LFMC, assuming that LAI can also be accurately retrieved. Since the spectral response to DMC is masked in fresh samples but not in dry samples, Riaño et al. (2005) proposed obtaining annual estimates of spatially distributed DMC near the end of the driest season. They assume that this biomass estimate will remain relatively constant over time without a change in land cover.

Additionally, spectral indexes with absorption features sensitive to DMC could improve LFMC estimates (Ustin et al., 2012; Wang et al., 2011, 2013). Dry matter exhibits several absorption features in the reflected SWIR (Asner, 1998; Feret et al., 2008; Jacquemoud et al., 1995, 1996) which could be measured with narrow-band sensors.

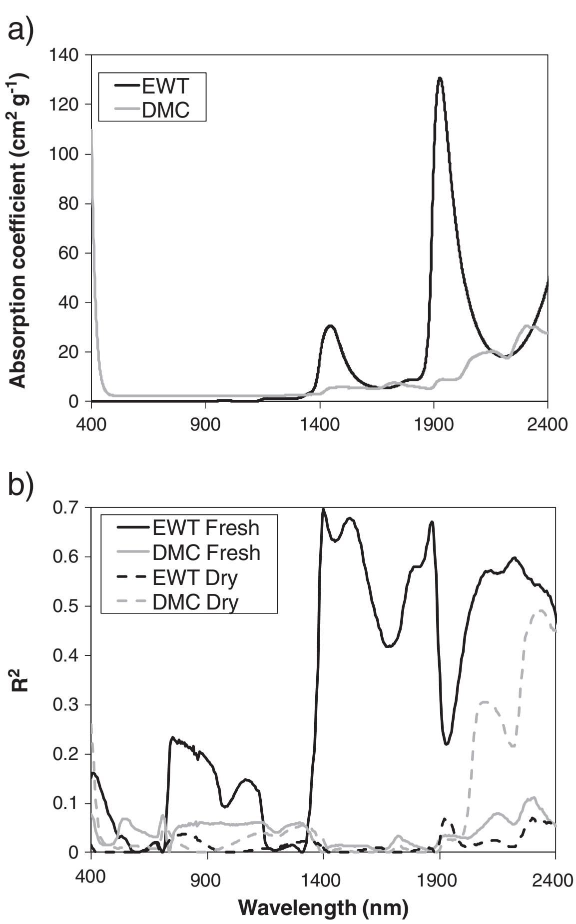

Fig. 2. a) Spectral absorption coefficients for water and dry matter (cm^2 g^{-1}) used in the PROSPECT leaf model (version 4 (Feret et al., 2008)) and b) correlation between EWT and DMC for each wavelength. DMC had little effect on reflectance of fresh leaves; therefore, radiative transfer modeling may be limited in providing a good estimation of DMC for fresh leaves. Figure adapted from Riaño et al. (2005).

To retrieve DMC, several multispectral indexes have been developed like the Cellulose Absorption Index (Nagler et al., 2000), the ASTER-defined Lignin-Cellulose Absorption index and the improved Shortwave-Infrared Normalized Difference Residue Index (Serbin et al., 2009). These three spectral indices were designed to estimate the coverage of dry non-photosynthetic vegetation (plant litter or crop residue) over bare soil, and not DMC of living foliage.

Two dry matter indices were developed based on the spectral differences between DMC and EWT (Romero et al., 2012; Wang et al., 2011, 2013). The Normalized Dry Matter Index (NDMI) is based on one narrow absorption feature of dry matter (1722 nm) at which the specific absorption coefficient of dry matter is greater than that of water (Wang et al., 2011, 2013). The effect of DMC on simulated leaf reflectance may be seen by a change in the slope of reflectance spectra at 1710–1750 nm (Fig. 1). Romero et al. (2012) found that the normalized difference ratio $(\rho_{2305} - \rho_{1495})/(\rho_{2305} + \rho_{1495})$, where ρ is reflectance and the subscript is wavelength in nm, also estimated DMC, because the absorption coefficient of dry matter at 2305 nm is greater than that of liquid water. While the absorption coefficients of dry matter may be greater than water at 1722 and 2305 nm, it is not certain that these indices could be used to measure canopy DMC because there is often more liquid water than dry matter in leaves.

Wang et al. (2013) hypothesized that the ratio of a spectral water index and a spectral dry matter index would be related to LFMC since LFMC is the ratio of EWT/DMC. The relationships between index ratios and LFMC were significant but non-linear (Wang et al., 2013). The ratio of the NDII6 (Table 3) to NDMI produced particularly strong correlations. Experimental data at the leaf scale validated this approach (Wang et al., 2013), but future research needs to be done at the canopy scale with narrow-band sensors. It is currently unclear how uncertainty in retrieved DMC and EWT will affect accuracy of combined LFMC estimation.

6.1.2. Confounding effects of LAI and other canopy variables

At the canopy level, the retrieval of LFMC from RS data needs to discriminate the influence of leaf structure, LAI and fraction coverage on plant reflectance (Ceccato et al., 2002b; Zarco-Tejada et al., 2003). CWC is the product of leaf EWT and LAI (Eq. 5), but LFMC is independent from LAI and may remain constant while LAI varies spatially or temporally. Weak relationships between LFMC and spectral reflectance are expected when there is also variation in LAI, as this factor has a stronger influence on canopy reflectance (Bowyer & Danson, 2004), but if LAI changes slowly over space and time, strong relationships between spectral reflectance and LFMC may be expected (Al-Moustafa et al., 2012). This was confirmed in the physical model-based study of Danson and Bowyer (2004) which showed that when a canopy reflectance model was driven by site-specific biophysical data with a narrow range of leaf DMC and LAI, statistically significant relationships between VIs and LFMC were obtained.

LAI significantly affects NDII, an index sensitive to water absorption, for a constant EWT value. But if the EWT $*$ LAI product (CWC) is constant, NDII also remains quite stable. PROSAIL simulations in Fig. 3 demonstrate the above statement. NDII6 varies broadly (0.105–0.389) for the same EWT (0.01 g/cm^2) when LAI (1–5) and therefore CWC (0.012–0.060 g/cm^2) is varied (Fig. 3, left). On the other hand, NDII6 would have similar values (0.326–0.404) for the same CWC (0.05 g/cm^2) even though EWT changes (Fig. 3, right). In this case, CWC is kept constant by simultaneously changing EWT and LAI.

Spatial heterogeneity of vegetation within a pixel is a major issue for estimating LFMC and for comparing estimated LFMC with ground measurements (Qi et al., 2012). For heterogeneous areas such as savannah-like environments, LFMC estimated from RS data will not represent LFMC for a single species, but rather an aggregate LFMC for the area measured by the sensor. There is potential for using spectral mixture analysis (SMA, Shimabukuro and Smith (1991)) to estimate

LFMC at the subpixel level and to improve methods to aggregate samples from different endmembers (species). When species vary spatially, a different set of endmembers could be appropriate to estimate LFMC at the subpixel level for each species, in what is called multiple endmember SMA (MESMA, Roberts et al. (1998)). Relative SMA (RSMA, Okin (2007), Okin et al. (2013)) might be another option when fraction of each endmember changes over time within the same pixel. Another possibility is that two pixels might have the same species composition with the same LFMC but different fraction of soil cover. To account for this, Huang et al. (2009) isolated the vegetation surface reflectance from the soil signal using SMA to estimate in their case corn and soybean water content independent of the soil fraction. Finally, operational LFMC from MODIS or other coarse spatial resolution optical image data is most affected by heterogeneous vegetation type composition within the ground resolution element. For example, natural forest could contain in the same pixel irrigated agriculture and each vegetation type would have a different seasonal behavior. LFMC of the natural forest would be impacted by the irrigated agriculture, so it would also need to be spectrally unmixed.

6.2. Methodological challenges

Both physical model-based (RTM) and statistical (empirical) methods to estimate LFMC from RS data have considerable limitations.

6.2.1. Site-specificity of statistical methods

Due to the site-specificity of statistical methods, empirical relationships cannot be applied to regional or global scales due to spatial differences in leaf and canopy characteristics, soil background, sensor characteristics and observation conditions (Dennison et al., 2005; Garcia et al., 2008; Riaño et al., 2005; Yebra et al., 2008a). Dennison et al. (2005) demonstrated that the best fit linear regressions of LFMC versus NDVI were site dependent (Fig. 4). Garcia et al. (2008) combined AVHRR and meteorological data for estimating LFMC. Their model showed good performance in grassland and shrubland but the authors stated that the application of the models to areas with different vegetation types/species may provide an unreliable estimation of LFMC.

Although statistical methods may be site specific, models based on heterogeneous sites or on multiple sites may capture broad relationships between remotely sensed variables and LFMC. Peterson et al. (2008) estimated LFMC using MODIS reflectance data by calibrating empirical equations which accounted for site-specific and inter-annual differences in vegetation amount and condition. Two new independent variables were added to a multiple linear regression analysis: an additive VI summary statistic variable, and a multiplicative VI summary statistic variable. This allowed the regression model to be used for a given functional type. Similarly, Caccamo et al. (2012b) aimed to account for differences in site-specific properties and calibrated a statistical model based on the maximum–minimum normalization of VARI and NDII6.

Researchers have also investigated new statistical methods to improve statistical model performance. Stow and Niphadkar (2007) normalized time series MODIS VIs using rescaling based on time series maximum and minimum VI values within each pixel. Max–min scaling reduced the effects of spatial and interannual varying vegetation cover, in order to relate changes of LFMC to meteorological drivers and also reduced errors in LFMC estimates. Kogan et al. (2003) used a similar approach assessing vegetation health in response to drought using AVHRR NDVI time series. Li et al. (2008) demonstrated the potential of genetic algorithms coupled with partial least squares (GA-PLS) in retrieving EWT and CWC. Zhang et al. (2011) introduced orthogonal signal correction-partial least square regression (OSC-PLSR) to extract EWT and LFMC from lab-measured reflectance spectra. The OSC-PLSR model showed good prediction for LFMC and reduced model complexity compared to simple PLSR. Additional surface measurements such as soil moisture may also provide opportunities for improving remote estimation of LFMC (Qi et al., 2012).

6.2.2. Constraining parameters of physical model-based approaches

Since RTM are based on physical relationships that are independent of sensor or site conditions, they should be more universal than empirical models. However, the selection and parameterization of RTM are far more complex than empirical models, since they require as inputs plant physiological and structural variables that are not always available, and are based on assumptions that may not accurately resemble conditions found in nature (e.g., Lambertian broad-flat leaves, semi-infinite horizontally homogeneous plant canopies), especially when complex canopies are involved. Finally, physical models (i) present uncertainties in the inversion mode, since very similar reflectances can be derived from a different set of input parameters, which is the well-known ill-posed inverse problem (Garabedian & Paul, 1964) and (ii) do not take into account ecophysiological relations, and therefore they might provide poor estimations when unrealistic combinations of input parameters are considered.

A priori knowledge of plant biophysical parameters should be used to constrain the input parameters of the RTM to model conditions as closely as possible to the actual canopy state (Combal et al., 2002a). Some authors have chosen to include data derived from satellite imagery as input parameters (Zarco-Tejada et al., 2003). Others have relied upon experimental data in controlled conditions (Riaño et al., 2005; Yebra & Chuvieco, 2009a). Yebra and Chuvieco (2009a) and Yebra et al. (2008b) proposed using ecological rules observed on the field to avoid simulating unrealistic spectra derived from combinations of parameters never met in nature. Using these ecological rules in simulation models significantly decreased the residual estimation error (RMSE = 19.77%) when compared to models run randomly

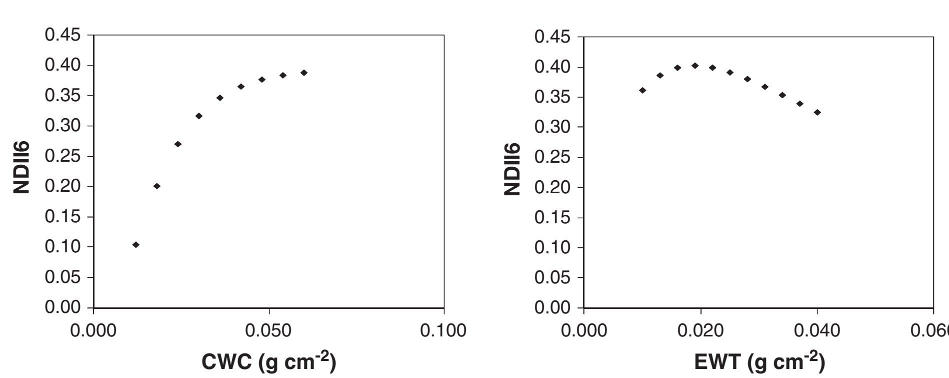

Fig. 3. PROSAIL simulations. Constant EWT = 0.01 g/cm^2 and variant LAI = 1–5 and therefore variant CWC = 0.012–0.060 g/cm^2 (Left). Constant CWC = 0.05 g/cm^2 by varying simultaneously EWT = 0.01–0.04 g/cm^2 and LAI = 1.25–5 (Right). For both cases leaf internal structure parameter was held constant at 1.5, leaf chlorophyll a + b content = 33 mg/cm^2, DMC = 0.02 g/cm^2, hot spot = 0.001, plagiophile leaves, sun angle = 25°, view angle = 5°, relative azimuth angle = −30°.

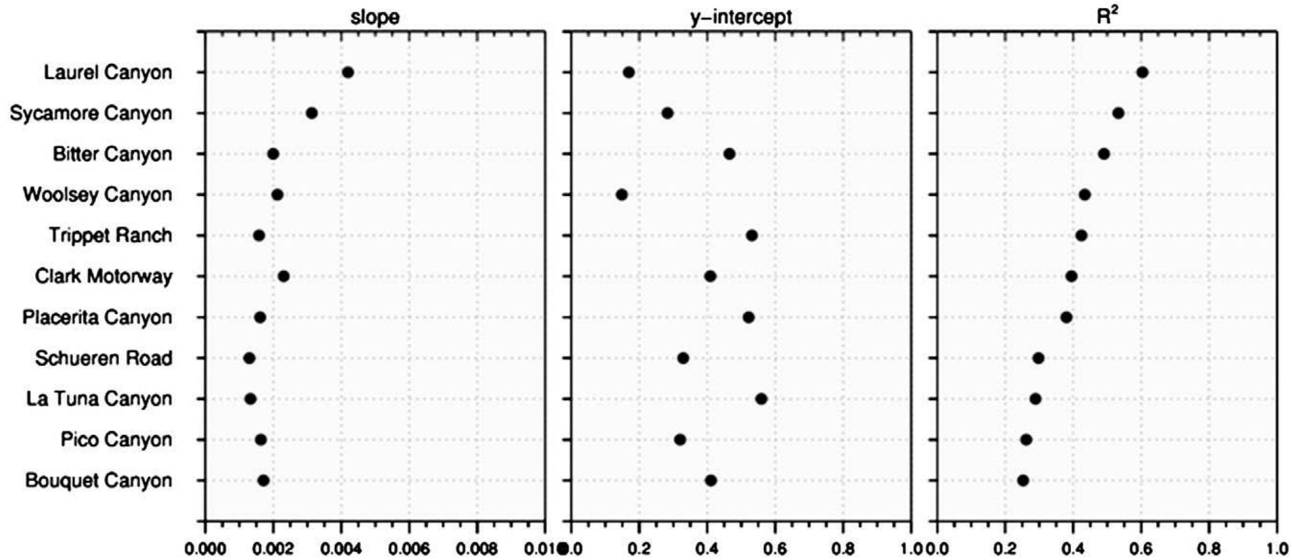

Fig. 4. Slope, y-intercept and R^2 values for the best fit linear relationship between LFMC (%) and NDVI for chamise (*Adenostoma fasciculatum*) at 11 sites sampled by the Los Angeles County Fire Department. Data from Dennison et al. (2005).

combining the input parameters (RMSE = 64.93%) (Yebra & Chuvieco, 2009b).

Recently Jurdao et al. (2013) made an exhaustive exploration of data sources to include ecological criteria in an RTM and estimated LFMC in woodlands of two different climatic regions of Spain. In an attempt to find the maximum accuracy, the authors fixed LAI and canopy coverage of vegetation (Ccov) in the inversion using different remote sensing products. However, these steps did not improve their results.

Since all these RTM studies are based on *a priori* knowledge of plant biophysical parameters to represent realistic situations, the RTM models calibrated this way can be applied to other areas without affecting the accuracy of the estimations.

However, Pingheng and Quan (2011) pointed out that all these approaches of alleviating the ill-posed problem based on a priori knowledge of plant biophysical parameters can restrict the operational utility of model inversion. To overcome this issue, the authors applied a separate merit function for each of the RTM input parameters based on specific wavelengths determined by sensitivity analysis. Extensive validations based on both *in situ* measured data sets and a RTM-simulated data set suggested that these procedures can substantially improve the inversion model performance and strongly reduce the "ill-posed" problem. However, this procedure needs to be applied and tested at the canopy level.

6.2.3. Dependence of physical model-based accuracies on inversion procedure

Another critical aspect of retrieval of LFMC is that RTM performance has a strong dependency on the inversion procedure used. Yebra (2008) compared two different merit functions of similarity between observed and simulated spectra (relative minimum quadratic distance ($RMSE^*_p$) and minimum spectral angle (SA), Table 2) and concluded that the use of the SA criteria provides a more consistent measure of spectral similarity which led to a more accurate estimation of LFMC, with RMSE and R^2 of 14.6% and 0.63 versus 22.43% and 0.36 using $RMSE^*_p$ (Fig. 5).

7. Main problems for the operational use of RS derived LFMC models

7.1. LFMC estimation error

Errors in LFMC estimation may directly affect safety and resource costs associated with prescribed fire and wildfire suppression (Weise et al., 1998), depending on the sensitivity of the fire behavior model to LFMC. The most widely used fire spread model (Rothermel) is highly sensitive to LFMC in most fuel types and Jolly (2007) for example found that a 10% difference in LFMC could produce up to 1200% difference in predicted ROS. Fire managers using LFMC models must be aware of the uncertainties involved in LFMC estimation, and how this uncertainty can affect the accuracy of fire spread predictions and fire risk estimation. Additionally, a formal evaluation program for LFMC estimation methods should better guide end-users to decide which model-product they should use in accordance with the accuracy needed.

Several published studies (Table 1) report LFMC estimation accuracies against field measured LFMC using the coefficient of determination (R^2), the root mean square error (RMSE) or mean absolute error (MAE). However, a conclusive comparison between studies is not possible due to the many differences in methodology and accuracy reporting. For example, these studies have differences in: i) calibration and validation procedures (e.g. RMSE sometimes reflects site-based or multi-site parameter fitting, sometimes independent cross-validation); ii) the input data used (sensor, RS product and collection); iii) the number, location, and type of field sites considered; and iv) protocol for field sample collection and processing. Future scientific studies should strive to use independent datasets to assess accuracy and report errors rather than R^2 values.

In general terms, LFMC of shrublands can be retrieved with higher accuracy than LFMC of grasslands and woodlands. Focusing on the studies that performed an independent validation (10 of 18 from Table 1), errors reported ranged between 8 and 20% for shrublands (Caccamo et al., 2012b; Garcia et al., 2008; Yebra & Chuvieco, 2009b), 25–61% for grasslands (Chuvieco et al., 2004c; Garcia et al., 2008; Yebra et al., 2008b) and approximately 30% for woodlands (Jurdao et al., 2013; Yebra & Chuvieco, 2009a). Higher errors may be reported for grassland species due to higher variability in LFMC for grasses over time.

Errors in estimated LFMC are critically important for determining fire risk. An error of 20% added to or subtracted from an estimated LFMC of 90% would result in shrubland fire danger ranging from low (ignition probability (IP) = 19% associated with a LFMC = 110%), to high (IP = 60% associated with a LFMC = 70%) when IP is calculated as in Chuvieco et al. (2004a). Dasgupta et al. (2007) evaluated the implication of uncertainties in LFMC for fire spread rate predictions using FARSITE fire behavior model (Finney, 1998). Their results showed that modeled fire spread rates for the pocosin fuel model when LFMC was

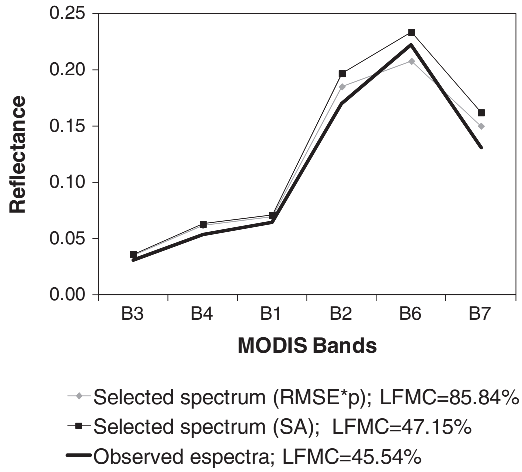

Fig. 5. Example of observed and simulated spectra using relative mean square error ($RMSE^*_\rho$) and spectral angle (SA) as merit functions. The simulated spectrum selected with the $RMSE^*_\rho$ is more similar in absolute terms to the observed spectrum than the simulated spectrum selected by the SA function. However the spectrum selected by the SA function corresponds to LFMC estimates closer to the observed value (Yebra, 2008).

below 100%, and maximum errors of 56% in LFMC estimation could produce an equivalent error in fire spread rate of 47 m h^{-1} for a no wind, no slope fire spread simulation.

7.2. LFMC and fire behavior

Some operational fire spread models (e.g. 1998) use fuel models containing spatially constant descriptions of LFMC. Use of spatially variable LFMC estimates provided by RS data can produce differences in modeled fire spread (Bossert et al., 2000). A challenge for fire behavior models that incorporate more complex descriptions of three-dimensional fuel distributions (e.g. Burgan, 1979; Linn et al., 2002; Mell et al., 2007; Morvan & Dupuy, 2004; Zylstra, 2011a,b) is estimation of LFMC within multiple fuel strata. In these situations, two-layer RTM, such as the Kuusk Markov Chain Canopy Reflectance Model (MCRM (Kuusk, 2001)) may prove useful. The Kuusk model considers that the vegetation is homogeneously distributed for each layer and uses leaf optical properties derived from the PROSPECT model (Jacquemoud, 1990). The canopy directional reflectance is generated based on the single scattering and diffuse fluxes from each layer, using direct and diffuse solar irradiance. The Kuusk model is more easily parameterized than other geometric models due to its assumptions of homogenous canopies, while still providing sufficient complexity through its inclusion of two vegetation layers with independent input conditions. On account of that, this model has been successfully used for fire severity modeling (Chuvieco et al., 2007; De Santis & Chuvieco, 2007). The use of 3D models (e.g. DART (Gastellu-Etchegorry et al., 2004) or FLIGHT (North, 1996)) should also be considered, although their parameterization would be significantly more challenging due to the large number of input parameters that are needed.

7.3. LFMC and fire risk

The conceptual definition of a fire risk assessment system should include the most relevant components associated with the fire process (Chuvieco et al., 2012). In relation to LFMC, another challenge is translating LFMC estimated using RS data into fire risk units to allow integration into a comprehensive fire risk assessment system. LFMC can be converted into fire risk using empirical models relating LFMC to fire occurrence, as discussed in Section 2. LFMC can also be translated into ignition probability (IP), where moisture of extinction (ME) identifies the minimum water content that prevents fire ignition. Fuels with LFMC values above ME would have low (or no) probability of being burned (Dimitrakopoulos & Papaioannou, 2001). This was the basis of using ME to convert FMC to IP in a fire risk assessment by Chuvieco et al. (2004a). The authors used an inverse linear function to obtain IP from ME, based on critical thresholds (105% for shrub species and 30% for grasslands) derived from experimental analysis. Jurdao et al. (2012) explored several methods to convert LFMC into IP considering climate (Mediterranean and Eurosiberian regions) and vegetation functional types (grasslands and shrublands). Non-parametric significance tests, histograms and percentiles, classification trees, and logistic regression models were used for estimating the IP from five variables based on LFMC. Logistic regression analysis was found to be the most advantageous modeling methodology, since it uses several predictor variables to compute a continuous probability of IP. Chuvieco et al. (2004a) and Jurdao et al. (2012) present regional solutions to estimating IP from LFMC, but methods that can be scaled globally could potentially be connected to global observations of fire occurrence (Justice et al., 2002). Additionally, an elevated probability of high fire occurrence does not necessarily imply a large number of fires or an extensive burned area, because when causal agents are absent, few or no fire events occur (Chuvieco et al., 2009).

8. Concluding remarks

Developing operational LFMC estimation is useful for improving fire risk assessment. Improved spatial and temporal monitoring of LFMC can potentially result in better allocation of fire protective resources and increase vigilance for fire hazard to people and property. This review demonstrates that recent research has addressed many issues constraining operational LFMC monitoring. Further advancement towards operational adoption of LFMC estimation can be realized in the following areas:

i) Improvements in spatial resolution and spectral dimensionality which have the potential to provide more accurate LFMC estimation. VIIRS represents an advance in spatial resolution over MODIS, while the planned HyspIRI mission could provide complementary improvements in the spectral domain.
ii) Progress in algorithm development may enhance the utility of LFMC estimates. Future work on statistical methods should focus on making them more robust across larger areas. Physical methods should improve retrieval of DMC and provide realistic ranges of parameters for solving the ill-posed model inversion problem.
iii) Most prior work has examined LFMC in Mediterranean ecosystems in Europe and Western North America. Further research is needed to assess the full utility of LFMC estimation across other fire-prone ecosystems.
iv) Reduction of error in LFMC estimates is needed to improve fire risk estimation and adoption by the end-user community. Integration of LFMC into fire behavior and fire risk models should include uncertainty produced by error in LFMC estimates.
v) An international effort is needed to create a network of field measurements for use in improving and validating LFMC estimates. The global database should use consistent methodology and be properly documented, georeferenced and publicly accessible.
vi) Research projects should go beyond scientific papers and should search for long-term operational viability of products and interaction with end-users.
vii) A formal evaluation program for methods of mapping LFMC should be organized to better guide end-users to assess which product or method for LFMC estimation best fits their needs.

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