Remote sensing estimation of vegetation moisture for the prediction of fire hazard

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Abstract. Various factors contribute to forest fire hazard, and among them vegetation moisture is the one that dictates susceptibility to fire ignition and propagation. The scientific community has developed a number of spectral indexes based on remote sensing measurements in the optical domain for the assessment of vegetation equivalent water thickness (EWT), which is defined as the weight of liquid water per unit of leaf surface. However, fire models rely on the live fuel moisture content (LFMC) as a measure of vegetation moisture. LFMC is defined as the ratio of the weight of the liquid water in a leaf over the weight of dry matter, and spectral indexes proposed so far fail in capturing LFMC variability. The aim of our research was to understand the potential and limitations of MODIS instruments on board Terra and Aqua satellites in retrieving LFMC. To this purpose, a dataset of synthetic reflectance measurements was constructed basing on PROSPECT and SAIL radiative transfer models. Isolines of LFMC were identified in the plane representing measurements in channels 2 (0.86 μm) and 5 (1.24 μm), leading to the definition of a novel spectral index that is directly related to LFMC, the Perpendicular Moisture Index (PMI). The PMI was validated against simulated and real reflectance measurements, showing that it is robust to all variable factors affecting canopy reflectance except leaf area index (LAI). An indirect validation was performed in the study area of Campania (13595 km2), Italy, where the values of PMI calculated from MODIS images at fire locations were confronted against a dataset of more than 6800 events recorded in 2000-2008. This analysis showed a clear relationship between PMI and fire propagation speed.

Keywords. Fire hazard, equivalent water thickness, live fuel moisture content, PROSPECT, SAIL, MODIS.

1. Introduction

Forest fires are a major threat to human life, economic development and the environment [1]. Fire managers need timely and reliable hazard maps to support them in the preventive allocation of resources. Several factors contribute to fire hazard, including the relative amount of fuels available for burning, their type and their moisture content [2]. Among these, fuel moisture is the most dynamic; it is also the most relevant, since it determines the forests susceptibility to fire ignition and propagation [3].

The evaluation of vegetation moisture from remote sensing measurements of reflected radiance in the solar spectrum relies on detailed studies of the optical properties of leaves [4]. A first measure of vegetation moisture is the “equivalent water thickness” (EWT), which denotes the content of water in leaf tissues. EWT is defined as the mass of water per unit area of leaf:

$$EWT = \frac{W_f - W_d}{A}$$

where Wf is the mass of the fresh leaf as measured in the field, Wd is the corresponding mass of the same leaf that has been oven dried, and A is leaf area. EWT is scaled to canopy level (EWTc) by simple multiplication by leaf area index (LAI) [5]:

$$EWT_c = EWT \times LAI \tag{1}$$

A different measure of vegetation moisture is live fuel moisture content (LFMC), which expresses the percentage weight of water in leaf tissues over the dry leaf weight:

$$LFMC = \frac{\left(W_f - W_d\right)}{W_d} \times 100$$

Considering that dry matter content (DMC) is defined as:

$$DMC = \frac{W_d}{A}$$

it is clear that:

$$LFMC = \frac{EWT}{DMC} \times 100 \tag{2}$$

LFMC is thus a measure of water relative to DMC, and as such it is not scaled to canopy level through LAI. In many vegetation types the mass of water exceeds that of the other leaf components, this meaning that LFMC values may be larger than 100%.

Both EWT and LFMC are valid measures of vegetation moisture, but they are not exchangeable, since from (2) a unique LFMC value can correspond to various EWT values, depending on leaf DMC. They are not even equivalent from a practical point of view: the forest fire research community is specifically interested in LFMC maps [6], since fire hazard and fire models depend on this measure of vegetation moisture [3].

Broadband spectral indexes proposed so far are sensitive to EWT, e.g. the Normalised Difference Infrared Index [7], the Normalised Difference Water Index [8], and the Global Vegetation Moisture Index [5]. However they generally do not provide the same level of accuracy in estimating LFMC [9].

The objective of the research described in this article was to understand whether spectral measurements from MODIS are able to capture the effect of LFMC variability on vegetation reflectance and whether this can be translated into a simple spectral index.

2. Materials and methods

2.1. Simulation of MODIS reflectance data

Simulated top of the canopy (TOC) reflectance spectra were produced coupling PROSPECT [10] and SAIL [11] radiative transfer models. Models input parameters were chosen from random uniform distributions, limited sets of values or fixed values, as specified in Tables 1 and 2. The adopted ranges were chosen to be wide enough to embrace a number of vegetation types and physiological conditions. The simulated dataset consisted of 1000 spectra, 100 for each of the LFMC values between 50 and 500% in steps of 50%. In order to simulate the values of LFMC in the specified steps, for each value of LFMC, EWT was first randomly chosen according to ranges in Table 1; the corresponding DMC value was then computed accordingly. The pair of values EWT + DMC was actually retained only if the calculated DMC was within the ranges in Table 1, otherwise a new couple of values was iteratively generated until the given constraints were met.

All produced spectra were converted to reflectance measurements in “land” channels 1-7 of Terra-MODIS using the instrument’s spectral sampling specifications [12]. Simulated datasets were finally perturbed with gaussian noise [13] to account for signal-to-noise ratio (SNR) of MODIS channels [14].

Table 1. Values of the parameters adopted to run PROSPECT.

	N	**C_{ab} (µg/cm^2)**	**EWT (g/cm^2)**	**DMC (g/cm^2)**
Dataset 1	Uniform [1,3]	Uniform [20,60]	Uniform [0.01,0.07]	Uniform [0.004,0.04]

Table 2. Values of the parameters adopted to run SAIL; observation geometry is set accordingly to MODIS specifications with random view angle along the scan line.

	LAI	**ALA**	**Hot-spot size**	**Soil spectrum**	**Sun zenith angle (deg)**
Dataset 1	Uniform [0.5,7]	Uniform [45,75]	0.001	Dark to medium	Uniform [40,60]

2.2. Development and validation of a spectral index

The definition of a spectral index sensitive to LFMC was based on the following steps:

- The simulated data points were plotted on all the possible Cartesian planes whose axes are couples of MODIS channels. The separability of clusters of points characterised by the same value of LFMC was calculated by means of the Jeffries-Matusita (JM) distance, and the plane allowing the best distinction was selected.
- Vegetation parameters other than LFMC causing the observed variability were recognised, and their effect on reflectance measurements was explored.
- Isolines of LFMC were identified.
- A spectral index for the quantification of LFMC was defined so that in the selected spectral plane its variation corresponded to a displacement perpendicular to isolines of LFMC.

To evaluate the proposed index against independent data, the LOPEX database was used [15]. The database includes leaf reflectance, leaf transmittance, EWT and DMC for 335 samples from 67 plant species. Leaf spectral measurements were scaled to TOC reflectance using the SAIL model, adopting random parameters as for the simulated dataset (Table 2), and then converted to MODIS measurements.

Indirect validation of the proposed spectral index can be performed by comparing PMI computed from Terra-MODIS reflectance data (MOD09 product) recorded at fires' locations in the day prior to the event against fire properties. To this purpose, the Italian Forest Corps (Corpo Forestale dello Stato, CFS) provided a dataset of more than 6800 fire records covering years between 2000 and 2008. Data included date and time, coordinates, duration, extent and presumed causes of each event.

3. Results

3.1. Exploration of simulated MODIS reflectance data

The pair of channels ch2-ch5 (Figure 1) shows the best separability of clusters of points with the same LFMC value among all possible couples of bands (average JM distance is 0.57). The dispersion of each group causes clusters to overlap with its neighbours; nevertheless the positions of the centres of each cluster appear to be ordered from lower to higher LFMC values.

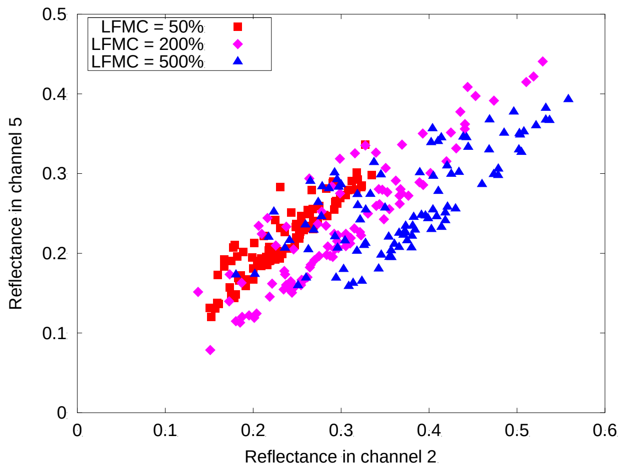

Figure 1. Distribution of simulated data points in the combinations of two MODIS channels 5 and 2. Only points corresponding to LFMC values of 50, 200 and 500% are plotted for clarity.

For each cluster of points with the same value of LFMC, the observed dispersion in the ch2-ch5 plane appears to depart from a dense alignment of points towards lower values of reflectance in channel 2. The most dispersed group in Figure 1 appears to be the one with LFMC = 500%. Figure 2 shows all the points of dataset 1 with LFMC = 500% plotted in the ch2-ch5 plane, adopting different symbols depending on the values of LAI (LAI<2, 2<LAI<4 and LAI>4). Points are plotted alongside the soil line obtained from soil spectra used in SAIL simulations.

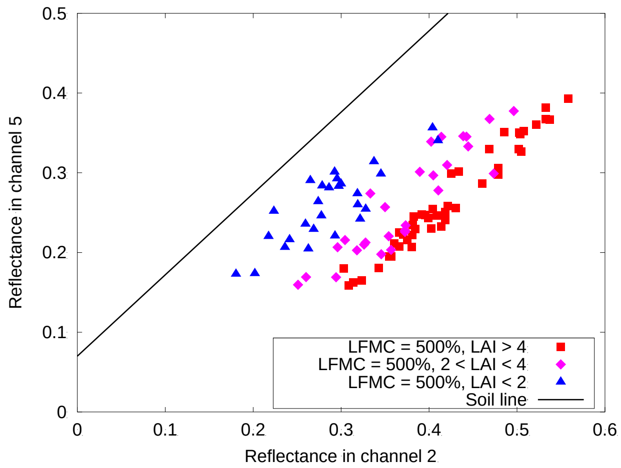

Figure 2. Distribution of simulated data points with LFMC = 500% in the ch5 vs ch2 plane. Points are plotted alongside the soil line, and grouped basing on LAI value.

The graph shows that when the vegetation cover is dense (LAI>4), data appear to concentrate along a straight line. With decreasing values of LAI, more background soil is exposed, and points shift towards the soil line. This effect is particularly strong when LAI<2.

A subset of the points in Figure 1, corresponding to LAI>4, were plotted again in Figure 3, alongside the soil line. When vegetation cover is dense, points with a constant value of LFMC align on straight lines with little variability. Such lines shift towards lower NIR and higher SWIR reflectance values with decreasing LFMC. These considerations clearly hint at the existence of isolines of LFMC, at least in conditions of dense vegetation cover.

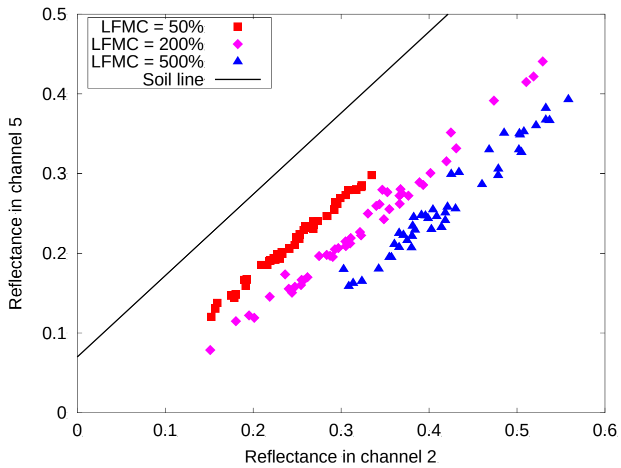

Figure 3. Distribution of simulated data points the ch5 vs ch2 plane. Only points corresponding to LFMC values of 50, 200 and 500% and LAI>4 were plotted, alongside the soil line.

3.2. Sensitivity of MODIS spectral reflectance to vegetation moisture

The observations in the previous sections were further formalised by computing the regression lines for each of the 10 simulated LFMC values (from 50 to 500% in steps of 50%), separately considering all simulated data, data with LAI>2, and data with LAI>4. Regression coefficients and intercepts of the regression lines are reported in Table 4 along with their 95% confidence intervals. All regressions are linear and significant with $p<0.001$.

The observations in the previous section are here confirmed: provided that the LAI is high enough, isolines of LFMC exist in the ch2-ch5 plane. The strength of the regressions decreases with a decrease in LAI or an increase in LFMC. Isolines can be safely assumed to be parallel. This assumption appears to be always true when LFMC<200%, and stays valid for higher values of LFMC only for increasing values of LAI.

3.3. Development and validation of the LFMC related spectral index

In the construction of any spectral index, maximum sensitivity is achieved when measuring property variation perpendicularly to its isolines. Being LFMC isolines parallel straight lines, the desired spectral index must measure the displacement of points along a straight direction. Since there is no preference among parallel lines, it is correct to evaluate LFMC variations as the distance of the measured reflectance from an a priori identified reference line. Such line can be assumed to be that of completely dry vegetation, i.e. LFMC=0% and EWT = 0. We call this the perpendicular moisture index (PMI), and we calculate it as:

$$PMI = -0.73 \times (R5 - 0.94 \times R2 - 0.028)$$

where *R2* and *R5* are reflectance values measured in channel 2 and channel 5 respectively.

Table 3. Coefficient of determination and slope of regression lines in the ch2-ch5 plane. Results for all data have been reported as well as for subsets based on LAI value. All regressions are significant with $p<0.001$.

	All data			LAI > 2			LAI > 4		
LFMC	**R^2**	**Slope**	**Intercept**	**R^2**	**Slope**	**Intercept**	**R^2**	**Slope**	**Intercept**
50	0.85	0.88±0.07	0.011±0.018	0.95	0.94±0.05	-0.011±0.012	0.99	0.95±0.02	-0.019±0.006
100	0.81	0.83±0.08	0.011±0.022	0.97	0.92±0.04	-0.027±0.011	0.99	0.94±0.03	-0.038±0.008
150	0.79	0.90±0.09	-0.024±0.026	0.97	0.96±0.04	-0.054±0.012	0.99	0.92±0.03	-0.040±0.009
200	0.82	0.86±0.08	-0.023±0.026	0.96	0.96±0.04	-0.070±0.014	0.99	0.95±0.03	-0.072±0.011
250	0.73	0.78±0.09	-0.001±0.031	0.95	0.94±0.05	-0.073±0.017	0.97	0.96±0.05	-0.085±0.018
300	0.76	0.72±0.08	0.018±0.029	0.90	0.93±0.07	-0.07±0.027	0.97	0.98±0.06	-0.110±0.023
350	0.61	0.65±0.10	0.027±0.037	0.85	0.84±0.08	-0.059±0.030	0.96	0.94±0.05	-0.107±0.021
400	0.56	0.62±0.11	0.033±0.040	0.83	0.83±0.09	-0.058±0.033	0.96	0.96±0.06	-0.122±0.022
450	0.72	0.67±0.08	0.011±0.032	0.90	0.83±0.06	-0.067±0.025	0.96	0.91±0.05	-0.110±0.023
500	0.52	0.51±0.10	0.071±0.038	0.81	0.83±0.09	-0.073±0.039	0.96	0.94±0.06	-0.131±0.027

The PMI was initially validated against simulated data. Table 4 reports the equations of regression lines and the coefficients of determination between this index and LFMC. The regression appears to be linear, and the PMI is capable of explaining increasing percentages of LFMC variability with increasing values of LAI.

Table 4. Regression laws and coefficients of determination of the PMI in predicting LFMC evaluated against simulated data.

	Regression law	**R^2**
All data	PMI=0.023+0.00014*LFMC	0.32
LAI > 2	PMI=0.028+0.00016*LFMC	0.70
LAI > 4	PMI=0.031+0.00018*LFMC	0.87

Independent validation was performed against LOPEX data scaled to canopy reflectance with SAIL model. The regression equations and the coefficients of determination of PMI vs LFMC on this dataset are reported in Table 5. The observed regressions are not linear, and lower performance is observed as compared with validation against the simulated dataset. Nevertheless, good coefficients of determination are observed for LAI values larger than 2.

Indirect validation was performed by associating each fire in the database provided by the CFS to the PMI value calculated at its location from the MODIS image in the day prior to fire event. LFMC values actually dictate rate of spread. However, this fire property is also affected by other factors, such as topography, vegetation type and amount, local winds, human intervention. Moreover, it varies in different points of the front of the same fire. However, for this research we were provided with fires' size and duration, which allowed the calculation of an average rate of spread.

Table 5. Regression laws and coefficients of determination of the PMI in predicting LFMC evaluated against LOPEX based simulated sensor reflectance.

	Regression law	R^2
All data	PMI=-0.14+0.030*log(LFMC)	0.39
LAI > 2	PMI=-0.16+0.036*log(LFMC)	0.56
LAI > 4	PMI=-0.18+0.041*log(LFMC)	0.63

To isolate the role of vegetation moisture from that of all the other factors, the PMI values associated to fires were divided into bins delimited by their 0th, 10th, …, 100th percentiles. Within each bin, the mean value of the rate of spread was associated to the corresponding median value of PMI. In Figure 4 the relationship existing between PMI and rate of spread computed as described is evident. The two parameters are clearly related by a linear regression law.

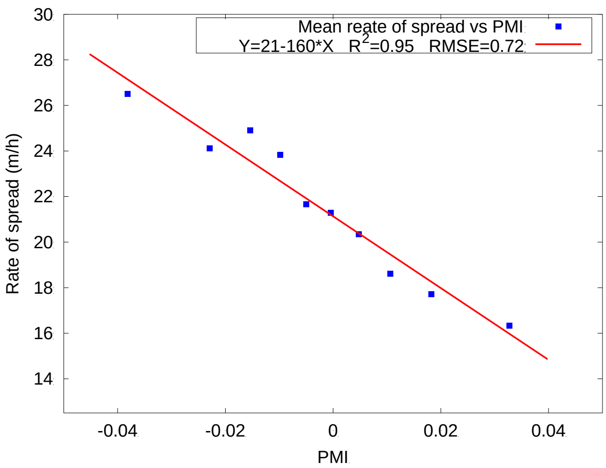

Figure 4. Relationship between average rate of spread and PMI, calculated from actual MODIS data and fire events.

4. Conclusions

The research exposed herein tried to solve the problem of LFMC estimation from MODIS measurements by first identifying how LFMC variations affect the reflectance in the spectral space of the seven "land" bands, and then deriving an index formula so that its isolines are intersected by displacement of points that occur when this property changes. It is shown evidence that the plane obtained by combining channel 2 (NIR) with channel 5 (SWIR) provides clear separability for group of points characterised by the same LFMC value (Figure 1).

These observations are in line with previous analyses of reflectance sensitivity to vegetation parameters. DMC and EWT largely affect vegetation reflectance in the NIR and SWIR wavelengths

[5, 16]. The more evident effect of LFMC variation in band combination 2-5 is due to the fact that reflectance sensitivity to EWT and DMC is weaker at longer SWIR wavelengths [17].

Points with the same value of LFMC lay on straight and parallel lines, at least for high LAI values (Figure 3). Lines of decreasing values of LFMC are shifted towards lower reflectance values in channel 2 and higher in channel 5. This means that a point in this spectral space is actually displaced when LFMC changes. To detect and quantify such displacement, the PMI measures the distance of reflectance points from a reference line, that of completely dry vegetation (LFMC = 0%).

The LAI appears to be the main factor influencing the quality of the relationship between the PMI and LFMC (Tables 3, 4, 5). Good results are achievable when LAI>2, which is a typical condition in a large variety of vegetation associations prone to fires such as those in mediterranean ecosystems. With decreasing values of LAI, the accuracy in the PMI vs LFMC relationship decreases. This is explained by the fact that reflectance in the SWIR is largely affected by this factor [17].

Dispersion of points away from the observed isolines is towards lower reflectance values in channel 2 and higher in channel 5. This is due to the fact that most soils show reflectance values in MODIS channel 5 higher than in channel 2 [8], while dense green vegetation exhibits the opposite behaviour. When LAI diminishes, more soil is exposed to sensor view and contributes to TOC reflectance, thus causing the displacement of points toward lower NIR and higher SWIR reflectance.

Table 3 shows that the coefficient of determination of the PMI vs LFMC relationship decreases with increasing values of LFMC, and that this effect is more evident with lower values of LAI. Recalling that an increase in LFMC can be due to both an increase in leaf EWT or a reduction in DMC can explain this observation. Indeed, the first cause implies a reduction in SWIR reflectance, and thus an increase of reflectance contrast between the leaves and the background soil, while the second increases both NIR and SWIR reflectance, increasing reflectance contrast in the NIR. Clearly, greater contrast results in a larger displacement of points towards the soil line when LAI diminishes.

The soil line and the dry vegetation line appear to be parallel in our experiments. This means that it is not possible to introduce modification to the index in order to make it robust to LAI variations; nevertheless, this finding can be taken into account within the framework of the specific application [18]. Both the reduction of LAI and the reduction of LFMC have the same effect in the ch2-ch5 plane, i.e. points are shifted towards the dry vegetation reference line. This means that when LAI is lower, the PMI underestimates vegetation moisture. This can be considered safe when the application of the PMI is in the field of fire prevention, where a missed alarm may have worse consequences than a false alarm.

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