FIRE RISK ASSESSMENT: THE ROLE OF HYPERSPECTRAL REMOTE SENSING

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ABSTRACT

The increasing demand for effective forest fire prevention instruments has faced operational and future Earth observation instruments with the challenge of producing updated and reliable maps of vegetation moisture. Various empirical band-ratio indexes have been proposed so far, based on multispectral remote sensing data, that have been found to be related to vegetation moisture expressed in terms of equivalent water thickness (EWT), which is defined as the weight of liquid water per unit leaf area. More sophisticated retrieval methodologies can be adopted when hyperspectral data are available, e.g. based on spectral curve fitting in selected water absorption bands or radiative transfer model inversion, allowing for better estimates of EWT. Problems arise with the evaluation of fuel moisture content (FMC), which is the percentage weight of water per unit of oven-dried leaf weight, due to its weak signal in vegetation spectrum. FMC is essential in fire models, and it is not interchangeable with EWT.

Basing on simulated vegetation spectra, this study aims at demonstrating that hyperspectral images of vegetated areas can be effectively used to evaluate FMC with accuracies not achievable with multispectral data. To this purpose, radiative transfer models PROSPECT and SAILH have been used to simulate canopy reflectance. Vegetation spectra have then been convolved to hyperspectral data basing on the design specifications of a formerly planned ASI-CSA hyperspectral mission (JHM configuration C), similar to those of the forthcoming PRISMA. For comparison against multispectral instruments, measurements from the Operational Land Imager (OLI) have also been simulated. Two retrieval methods have been tested, based on spectral indexes and on partial least squares (PLS) regression. The latter methodology is particularly suited to analyse high-dimensional data.

Results confirm that spectral indexes are good predictors of vegetation moisture expressed as EWT, but their performance in evaluating FMC is poor. By using PLS regression on hyperspectral data, a linear model can be built that accurately predicts FMC. No such result is achievable from OLI simulated data.

Key words: Fire hazard; vegetation moisture; hyperspectral remote sensing; PROSPECT; SAILH; PRISMA.

1. INTRODUCTION

Forest fires are a major environmental threat in the Mediterranean basin; a total area between 200000 and 600000 ha is burnt every year, with an average of 60000 fires reported each year [6]. The destruction of forests has a negative impact on carbon fixation, while soil erosion increases due to both the loss of canopy cover, which attenuates rainfalls and facilitates water percolation in the soil, and to the physic-chemical alteration of the soil surface. Economic costs are high as well, due to the reduction in the productive potential of forests and surrounding lands, with negative impact on regional economies and populations life quality, especially in the economically depressed areas.

It is believed that in the Mediterranean area 95% of fires are due to human activities [8]. Awareness-rising campaigns have shown to be successful in the reduction of unintentional fires, but the number of fraudulent fires still remains high, making it necessary the use of more sophisticated prevention strategies. Since human behavior (the ignition) cannot be predicted, fire managers are more concerned about fuel condition and its variation with time. This information is directly related to the ease of inception (fire hazard), the difficulty in fire suppression (fire danger) and the direction of propagation.

For a fire to spread it is required that fuel moisture and temperature are at an adequate level [18]. A forest fire hazard index synthesizes this information into a single value, providing a measure of ignition probability. Various factors contribute to the quantification of fire danger, including fuel type, fuel moisture, terrain aspect and slope, winds [7]; some of them are static (do not change with time), while others are dynamic. Among the latter, fuel moisture plays a key role, because it determines the forests susceptibility to fire ignition and propagation [18]. A higher moisture means a higher amount of heat needed to ignite a fuel, since more energy is necessary to evaporate water [4]. It also implies slower fire propagation, since part of the heat released by the flames is used to evaporate the water from the adjacent fuels [19]. For this reason a fast and reliable tool is needed by local authorities to forecast fire danger, allowing a sound allocation of intervention resources through risk modeling [1].

Vegetation moisture affects radiometric properties of live

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vegetation in a distinguishable way, that can be recorded by optical remote sensing instruments [3]. Various empirical band-ratio indexes have been proposed, based on multispectral remote sensing data, that have been found to be related to vegetation moisture measured as equivalent water thickness (EWT, g/cm^2), e.g. [17, 9, 22, 3]. This quantity is defined as the weight of liquid water in leaf tissues per unit of leaf area. More sophisticated retrieval methodologies can be adopted when hyperspectral data are available, e.g. based on spectral curve fitting in selected water absorption features [10] or on radiative transfer models inversion [19], allowing for improved estimates of EWT.

However, the fire research community is much more interested in vegetation water measured as fuel moisture content (FMC, %), which is defined as the percentage weight of liquid water in leaf tissues per unit of dry leaf weight. It is equivalent to the ratio of EWT over the dry leaf weight per unit area (dry matter content, DMC, g/cm^2). Its evaluation from spectral measurements is more problematic, as compared to EWT, due to the fact that it is the ratio of two parameters that independently affect vegetation reflectance. This causes broad-band spectral indexes to capture a smaller proportion of FMC variability, as compared to EWT, but more interesting results can be expected with the use of hyperspectral data.

In this study, two methodologies have been tested for the exploitation of hyperspectral measurements and the evaluation of EWT and FMC, with the help of simulated reflectance data. The first one was based on the use of spectral indexes related to vegetation moisture, initially developed for broad-band multispectral instruments. Results from their narrow-band equivalents calculated from hyperspectral measurements are compared against those achieved by the same indexes calculated from simulated broad-band measurements. The second experiment is based on the use of partial least squares (PLS) regression [21], which is suited to exploit the high dimensionality of hyperspectral measurements. Results from hyperspectral data will be compared against those achieved from the Operational Land Imager (OLI) on board the Landsat Data Continuity Mission, due for launch in December 2012.

2. SPECTRAL ESTIMATION OF VEGETATION MOISTURE

2.1. Measures of vegetation moisture

There are two different ways to express water content in vegetation tissues. The equivalent water thickness (EWT, g/cm^2) is defined as the weight of liquid water per unit leaf area:

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

where W_f is the weight of the fresh leaf as measured in the field, and W_d is the corresponding weight of the same leaf that has been oven dried. This parameter explains most of the variability of leaf spectral reflectance in the entire short-wave infrared (SWIR) domain [2], and it is directly related to absorption features at 970, 1200, 1450 and 1950 nm.

The fuel moisture content (FMC, %) is the percentage weight of water per unit of oven-dried leaf weight:

$$FMC = \frac{W_f - W_d}{W_d} \cdot 100$$

This quantity is related to fuel ignitability and fire behavior, and it is an essential input to fire models. FMC is equivalent to the ratio of EWT over the dry leaf weight per unit area (dry matter content, DMC, g/cm^2), which is defined as:

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

EWT and DMC affect vegetation spectra independently [3]. This complicates the retrieval of FMC from vegetation reflectance measurements, also in consideration of the fact that FMC variability causes little spectral variations that can be confounded among those caused by other influencing factors [10, 14]. For this reason, most researches on the remote sensing of vegetation moisture have concentrated on EWT and on the canopy EWT:

$$EWT_c = EWT \cdot LAI$$

which is a measure of the thickness of the equivalent layer of leaf tissues water within the pixel that would produce the observed reflectance. However, FMC is used in fire models for the prediction of ignition probability and fire behavior, and due to their different physical meaning, it is not interchangeable with EWT_c.

2.2. Remote sensing methods for vegetation moisture retrieval

A study on leaf spectral signature sensitivity to EWT and DMC [3] has shown that SWIR reflectance is mainly influenced by EWT, but also by leaf structure and DMC, while near infrared (NIR) reflectance is only sensitive to the latter two. This consideration has been the basis for the development of a number of spectral indexes based on NIR and SWIR wavelengths, where NIR reflectance serves as a normalizing factor to enhance SWIR response to leaf moisture. Despite the large number of spectral indexes developed so far, in this study only two indexes were taken into consideration. The Normalized Difference Water Index (NDWI), constructed basing on MODIS optical bands [9], is defined as:

$$NDWI = \frac{R_{860} - R_{1240}}{R_{860} + R_{1240}}$$

where R_{860} and R_{1240} are reflectance measures in bands centerd at 860 and 1240 nm respectively. More recently, the Global Vegetation Moisture Index (GVMI) has been developed basing on SPOT-VEGETATION data [3]:

$$GVMI = \frac{(R_{840} + 0.1) - (R_{1660} + 0.02)}{(R_{840} + 0.1) + (R_{1660} + 0.02)}$$

Our choice of these indexes is based on the fact that they rely on two different SWIR bands, and that most of the indexes found in literature are based on the same wavelengths. While NDWI bases its sensitivity to vegetation moisture on the reflectance around 1240 nm, the GVMI uses the band around 1660 nm. Researches have shown that both indexes are good indicators of EWT_c [5], although the produced humidity estimates are also sensitive to the leaf area index (LAI) of the observed vegetation [3, 16].

These indexes have in common the fact that they exploit the different sensitivities of NIR and SWIR reflectance to leaf biophysical properties to estimate leaf water content. They have been developed for broad-band multispectral instruments, although equivalent narrow-band spectral indexes can be defined. When hyperspectral measurements are available, the NIR-SWIR paradigm can be abandoned, and the additional information included in the data can be exploited by taking into account the physical processes influencing vegetation reflectance. In [10] a simplified vegetation reflectance model has been used to fit observed spectra with calculated spectra around the liquid water absorption feature at 970 nm and to calculate leaf EWT. In [19] the entire measured spectrum is used together with inverse radiative transfer modeling to retrieve EWT. However, these methodologies fail to provide accurate estimates of DMC [15], and thus of FMC.

For these reasons, we adopted a different approach, based on the Partial Least Squares (PLS) regression [21]. PLS is a particular type of multivariate analysis which is capable of modeling the underlying structure relating the predictor variable $\mathbf{X}$ (the observed spectra) to the response variable $\mathbf{Y}$ (in our case, the FMC), and it is particularly suited to analyse strongly collinear high-dimensional data.

The basic concept of PLS model is the definition of a reduced number of variables, called the X-scores and denoted by matrix $\mathbf{T}$. The X-scores are ortogonal, and are both a predictor of $\mathbf{Y}$ and a model of $\mathbf{X}$. The underlying assumption is that both $\mathbf{Y}$ and $\mathbf{X}$ can be modeled by the same "latent" variables. In matrix form, the X-scores are a linear combination of variables $\mathbf{X}$:

$$\mathbf{T} = \mathbf{X} \cdot \mathbf{W}^* \tag{1}$$

where $\mathbf{W}^*$ is the transformation matrix. The X-scores are also good predictors of variables $\mathbf{X}$:

$$\mathbf{X} = \mathbf{T} \cdot \mathbf{P}' + \mathbf{E}$$

where $\mathbf{P}'$ is the weights matrix and $\mathbf{E}$ are the residuals. The X-scores are simultaneously a predictor of $\mathbf{Y}$:

Table 1. PROSPECT simulation parameters

	min	max
N (adim)	1	3
C_{ab} ($\mu g/cm^2$)	25	80
EWT (g/cm^2)	0.01	0.03
DMC (g/cm^2)	0.01	0.04

Table 2. SAILH simulation parameters

	min	max
Soil reflectance	dark, medium, bright	
Hotspot size	0.001	0.01
LAI (m^2/m^2)	0.5	3
Leaf angle distribution	plagiophile, erectophile	
Sun Zenith angle (deg)	40	60
Sun Azimuth angle (deg)	180	220
View Zenith angle (deg)	-30	30

$$\mathbf{Y} = \mathbf{T} \cdot \mathbf{Q}' + \mathbf{F} \tag{2}$$

where $\mathbf{Q}'$ is the weights matrix and $\mathbf{F}$ are the residuals. By inserting (1) in (2) we obtain the multiple linear regression model:

$$\mathbf{Y} = \mathbf{X} \cdot \mathbf{W}^* \cdot \mathbf{Q}' + \mathbf{F} = \mathbf{X} \cdot \mathbf{B} + \mathbf{F}$$

To find the X-scores and the PLS regression coefficients $\mathbf{B}$ the Non-linear Iterative Partial least Squares (NIPALS) algorithm has been used [21].

3. DATASET

Experiments were based on synthetic vegetation spectra. Simulated data were produced by coupling PROSECT and SAILH models. PROSPECT [11] is a radiative transfer model for the simulation of reflectance and transmittance of plant leaves. Four parameters are required: chlorophyll a+b concentration C_{ab} ($\mu g/cm^2$), EWT (g/cm^2), DMC (g/cm^2), and a leaf structural parameter N. With this model a wide range of vegetation spectra can be simulated, corresponding to a variety of physiological conditions. In the present study, PROSPECT has been used to simulate 1000 vegetation reflectance and transmittance spectra, randomly choosing each simulation parameter from a uniform distribution whose minimum and maximum values are those reported in Tab. 1.

A second radiative transfer model, SAILH [20], has been used to scale leaf reflectance/transmittance to top of the canopy reflectance. Model parameters are leaf area index, leaf angle distribution and hot-spot size, soil background spectrum, skylight fraction, and view and illumination geometry. SAILH parameters for each of the simulated leaf spectra have been randomly chosen from the values in Tab. 2.

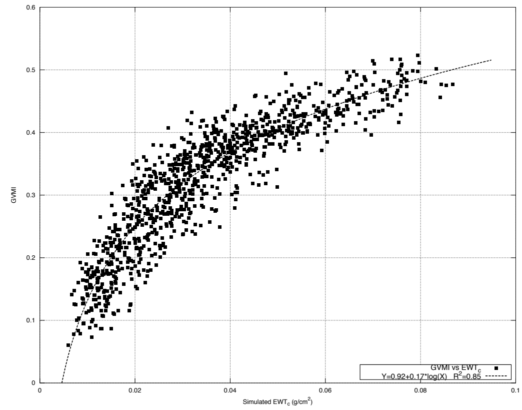

Figure 1. Relationship between EWT$_c$ and GVMI based on simulated hyperspectral measurements.

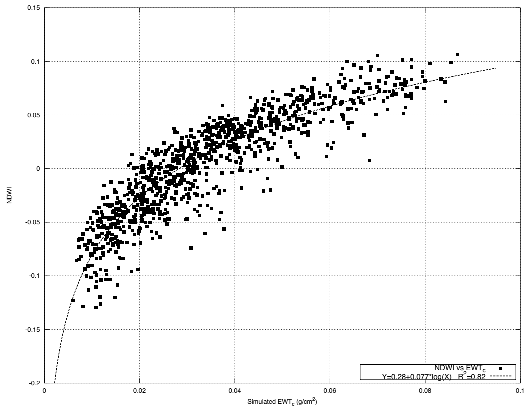

Figure 2. Relationship between EWT$_c$ and NDWI based on simulated hyperspectral measurements.

Simulated spectra were then convolved to satellite measurements basing on the design specifications of a formerly planned ASI-CSA hyperspectral mission (JHM configuration C), similar to those of the forthcoming PRISMA. For comparison against retrieval performance from typical multispectral data, OLI measurements onboard the planned Landsat Data Continuity Mission have been simulated as well.

4. RESULTS

4.1. Sensitivity of spectral indexes to vegetation moisture

The two spectral indexes introduced in the section 2 have been calculated using the corresponding narrow-band reflectance values from simulated hyperspectral data. Regression of calculated GVMI and NDWI against EWT$_c$ values show that both indexes are able to explain a large proportion of the variability of this parameter (Fig. 1 and Fig. 2). A performance comparison with OLI derived moisture estimates can only be based on the GVMI, due to the absence in this instrument of a band around 1240 nm. As shown in Fig. 3, OLI derived GVMI performance is very similar to that of the same index calculated from narrow-band reflectance. This underlines the fact that the use of spectral indexes calculated from hyperspectral data provides no greater accuracy in evaluating vegetation moisture as compared to the corresponding broad-band based indexes. The evaluation of FMC from both indexes provides much worse results ($R^2 = 0.09$, graph not shown), with no increase in accuracy provided by hyperspectral data.

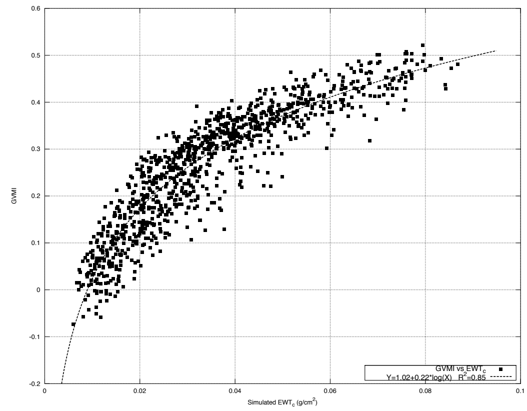

Figure 3. Relationship between EWT$_c$ and GVMI based on simulated OLI measurements.

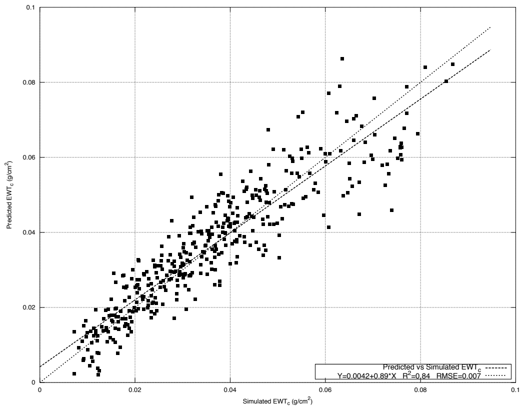

Figure 4. EWT$_c$ retrieval accuracy from simulated hyperspectral measurements using PLS regression.

4.2. PLS retrievals of vegetation moisture

Before preforming PLS regression, the samples were split into two sets: 600 samples picked at random were used to evaluate the X-scores and the regression coefficients with the NIPALS algorithm, while the remainder 400 samples were used to validate the regression. Nine latent variables were selected to describe the relationship between simulated and predicted values of both EWT$_c$ and FMC, being this number the one providing the best performance.

As shown in Fig. 4, PLS regression achieved good results in the prediction of the EWT$_c$; however, the accuracy is comparable to that of spectral indexes. This confirms the qualities of spectral indexes based on NIR and SWIR reflectance in the evaluation of EWT$_c$.

The PLS regression shows good results in the prediction of FMC (Fig. 5), with 87% of the variability caught by the model. The subtile signal in vegetation spectrum due to FMC is an information "hidden" in the high-dimensional hyperspectral measurements, and PLS regression appears to be able to catch its variability.

A previous research has shown that FMC retrieval accuracy is affected by vegetation density, with lower LAI values providing less accurate retrievals [13]. However, PLS seems to be robust against the "noise" in other vegetation paramaters. Fig. 6 shows that PLS regression can still model the relationship between measured spectra and FMC when only test samples with LAI<1 are selected.

5. DISCUSSION

The Remote Sensing community has long been involved in the estimation of EWT$_c$, since this paramater provides spectrally distinct features. However, the Fire Models research community is much more interested in vegetation moisture expressed as FMC, being this parameter directly

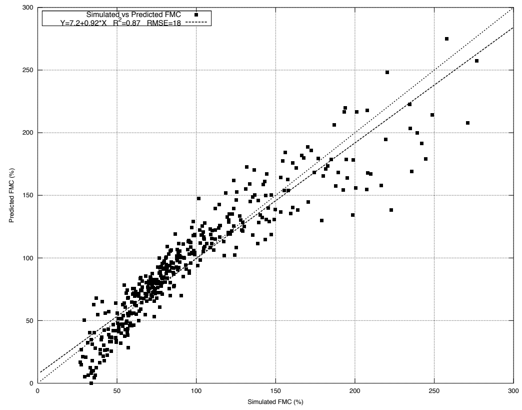

Figure 5. FMC retrieval accuracy from simulated hyperspectral measurements using PLS regression.

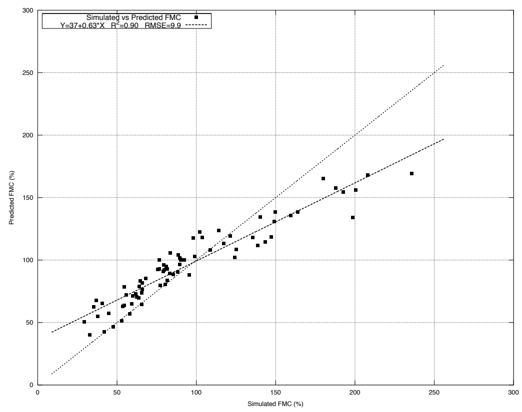

Figure 6. FMC retrieval accuracy from simulated hyperspectral measurements using PLS regression when only samples with LAI<1 are selected.

related to fire behavior. The advent of operational satellites carrying hyperspectral instruments opens new opportunities for the development of products aimed at the estimation of vegetation FMC and the characterization of forest fire hazard.

In this study, with the help of simulated vegetation spectra, we have shown how conventional spectral indexes developed for broad-band multispectral instruments are able to accurately evaluate EWT_c, but they are poor predictors of vegetation FMC, and no improvement is achieved when calculated from hyperspectral data.

The problem lies with the weak signal in vegetation spectra provided by FMC variability. To capture this variability, the PLR regression appears to be a valid methodology. Thanks to its use of the concept of "latent variables" related to both the independent and the dependent variables, PLS allows the construction of a linear regression model successfully linking hyperspectral measurements to FMC. A previous research has shown similar results based on leaf spectral measurements [12]. However, the authors have envisaged the need to first reduce data dimensionality (by selecting 44 to 54 channels) by means of genetic algorithms. In this study we show that there is no such need, since PLS is able to easily adapt to high-dimensional data, while fully capturing the desired relationship. This relationship also appears to be robust against factors that traditionally affect retrieval accuracy, such as low LAI values.

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