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Detecting vegetation leaf water content using reflectance in the optical domain

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Abstract

This paper outlines the first part of a series of research studies to investigate the potential and approaches for using optical remote sensing to assess vegetation water content. It first analyzes why most methods used as approximations of vegetation water content (such as vegetation stress indices, estimation of degree of curing and chlorophyll content) are not suitable for retrieving water content at leaf level. It then documents the physical basis supporting the use of remote sensing to directly detect vegetation water content in terms of Equivalent Water Thickness (EWT) at leaf level. Using laboratory measurements, the radiative transfer model PROSPECT and a sensitivity analysis, it shows that shortwave infrared (SWIR) is sensitive to EWT but cannot be used alone to retrieve EWT because two other leaf parameters (internal structure and dry matter) also influence leaf reflectance in the SWIR. A combination of SWIR and NIR (only influenced by these two parameters) is necessary to retrieve EWT at leaf level. These results set the basis towards establishing operational techniques for the retrieval of EWT at top-of-canopy and top-of-atmospheric levels.

Keywords: Leaf water content; Fuel moisture content; Optical domain; Shortwave infrared

1. Introduction

During the last decades, the repeated occurrence of severe wildfires affecting various parts of the world has highlighted the need to develop effective monitoring tools to assess and eventually mitigate these phenomena. Research on biomass burning has progressed from monitoring active fires using satellite data (Malingreau & Tucker, 1988; Flasse & Ceccato, 1996) to studying impacts of biomass burning on the environment (Levine, 1996). To understand biomass burning processes, it is essential to monitor the parameters that influence these processes, such as meteorological variables, amount of biomass, and vegetation water content. Remote sensing is advantageous for the detection of vegetation water content since it could provide an indication of fire occurrence risks and burning processes from a local to global scale.

The first step towards establishing an operational technique to retrieve vegetation water content using remote sensing is to clearly identify and demonstrate where the potential lies. This study investigates the first level at which water content influences a radiometric response, i.e. at leaf level. It initially discusses the suitability of existing remote sensing methods for assessing vegetation water content in the context of biomass burning and clarifies definitions that are commonly used. It then documents the physical basis supporting the use of remote sensing to directly detect vegetation water content in terms of Equivalent Water Thickness (EWT), and discusses a

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method for improving the accuracy in retrieving EWT at leaf level.

2. Assessment of existing remote sensing methods for estimating vegetation water content

The most practical, objective, and cost-effective way to monitor vegetation from a local to global scale is the use of Earth Observation technologies. Satellites can provide local to global coverage on a regular basis (almost daily for NOAA-AVHRR, SPOT-VEGETATION). They also provide information on remote areas where ground measurements are impossible on a regular basis. Different sensors are currently onboard Earth Observation satellites that may be applicable to the monitoring of vegetation water content. These sensors can be separated into the following three categories.

(1) *Visible to shortwave infrared* (SWIR, spectrum between 400 and 2500 nm). These provide information on vegetation biophysical parameters such as the chlorophyll content, the leaf area index, and the vegetation water content (Tucker, 1980).

(2) *Thermal infrared* (spectrum between 6.0 and 15.0 μm). These provide information on the thermal dynamics of vegetation cover. Thermal infrared has been used to estimate the evapotranspiration of vegetation canopies, a parameter that is closely related to water stress (Moran et al., 1994).

(3) *Radar* (spectrum between 0.1 and 100 cm). These provide information on the dielectric constant which could be related to vegetation water content (Moghaddam & Saatchi, 1999).

The following sections review and assess existing methods that use visible to SWIR and thermal infrared sensors to assess vegetation water content for the purpose of estimating risk of fire and burning processes. Methods that use radar sensors have not been included within the scope of this study.

In the biomass burning community, most research to date using optical and thermal infrared sensors has focused in three areas:

(i) The estimation of chlorophyll content or the degree of drying (curing) as an alternative to the estimation of vegetation water content.
(ii) The estimation of vegetation status as an alternative to the estimation of vegetation water content.
(iii) The direct estimation of vegetation water content.

2.1. Chlorophyll content/degree of drying (curing) vs. vegetation water content

A number of studies based on the relation between chlorophyll and water content have been carried out using remote sensing methods. These methods search for relationships between calculated vegetation indices and water content information (e.g. Eidenshink et al., 1990; Paltridge & Mitchell, 1990; Peñuelas et al., 1993; Alonso et al., 1996; Burgan, 1996; Illera et al., 1996; Chuvieco et al., 1999). Indices such as the Normalized Difference Vegetation Index (NDVI), the Relative Greenness Index (RGI), and the Global Environment Monitoring Index (GEMI), have been used to estimate vegetation moisture content and to provide information on risk of fire occurrence (e.g. Burgan, 1996; Illera et al., 1996; Paltridge & Barber, 1988; Chuvieco et al., 1999).

Researchers have typically assumed that the chlorophyll content of leaves or the degree of dying and drying out (also defined as degree of curing by Cheney & Sullivan, 1997) were proportional to moisture content (e.g. Tucker, 1977; Paltridge & Barber, 1988; Burgan, 1996; Illera et al., 1996). This assumption may be correct for some species but cannot be generalized to all ecosystems. Variations in chlorophyll content can be caused by water stress but also by phenological status of the plant, atmospheric pollution, nutrient deficiency, toxicity, plant disease, and radiation stress (Larcher, 1995). The following examples describe a few case studies where chlorophyll content is not related to water content. In a temperate forest, Gond et al. (1999) showed that there is no correlation between the chlorophyll and water content for five different species (*Rhododendron ponticum* L., *Quercus robur* L., *Molinia caerulea* (L.) Moench., *Pinus sylvestris* L., and *Prunus serotina* J.F. Ehrh.). In the case of *Q. robur*, *Pr. serotina*, and *Mol. caerulea*, chlorophyll concentration decreases in autumn (due to the phenological status of the plant), but the water content remains constant. In addition, Körner (1999) showed that the brownish overall appearance, which is common for alpine turfs in temperate zone climates, is not related to desiccation. He found that this phenomenon is due to normal leaf turnover, which, in graminoids, is associated with terminal leaf dieback. The rather rigid senesced leaf ends are not shed and decompose slowly, hence, the brownish appearance. This phenomenon is observed irrespective of microsite moisture. Conversely, maize plants (*Zea mays*) submitted to drought stress present some disturbances in the photosynthetic functioning of the plant without a change in the pigment concentration (Maracci et al., 1991). With increasing water deficiency, the net photosynthetic activity of the maize plants decreases by a factor of about 100, while the chlorophyll concentration of the samples, as well as the reflectance in the visible wavelength, remains almost unchanged.

Changes in water content are therefore not directly related to the chlorophyll concentration or the degree of curing for all types of vegetation. As such, the use of these criteria can only be used for small regions where the correlation between chlorophyll activity, degree of curing, and water content has been established. The use of low-resolution satellite data does not permit analysis at species level in most ecosystems because one pixel usually contains a mixture of several species. Indicators of vegetation water content, to be remotely sensed, must therefore be independent of species and preferably related to absolute vegetation water content.

2.2. Vegetation status vs. vegetation water content

Vegetation status is an indicator of the degree of stress experienced by plants in their environment (Larcher, 1995). Vegetation stress can be defined as any disturbance that adversely influences growth (Jackson, 1986). This stress can be due to many factors, one of which is a lack of water that restricts transpiration, inducing closure of stomata and resulting in less water evaporating from the leaf surface. Because less cooling occurs due to water evaporation, the temperature of the leaf increases (Jackson, 1986). As an alternative to measurement of vegetation water content to assess short-term fire risk, Chuvieco et al. (1999) investigated the possibility of using this thermal dynamic of vegetation. They assumed that differences between the air and surface temperatures were related to plant water content and to water stress. In line with this assumption, several indices have been proposed to measure vegetation stress due to a lack of water, such as the Crop–Water Stress Index (CWSI) (Jackson et al., 1981), the Stress Index (SI) (Vidal et al., 1994), and the Water Deficit Index (WDI) (Moran et al., 1994). These indices estimate vegetation status by measuring evapotranspiration. Indeed, the ratio of actual/potential evapotranspiration does appear to be a good indicator of vegetation status (Desbois et al., 1997). Moisture stress indices have also been developed combining satellite-based information on the relationship between NDVI, surface temperature, and air temperature, in association with production efficiency models (Goetz et al., 1999). However, vegetation status is not a direct measurement of vegetation water content. A case study using sunflower showed that the water content per unit leaf area generally does not change much due to moderate water stress since the plant tried to maintain a level compatible with its basic functioning (Beaumont, 1995). In fact, reducing transpiration helps to conserve available water (Larcher, 1995) as each species has developed different mechanisms to resist water stress. Although an important parameter for monitoring natural and agronomic plant productivity, vegetation stress is not suitable for the assessment of vegetation water content, as many species may show signs of reduced evapotranspiration without experiencing a reduction in water content.

Vegetation status is also measured either by the Relative Drought Index (RDI) (Höfler et al., 1941) or the Relative Water Content Index (RWC) (Inoue et al., 1993). RDI compares the actual Water Saturation Deficit (WSD_{act}) with the critical threshold value for the Water Saturation Deficit (WSD_{crit}) (Eq. (1)).

$$\mathrm{RDI} = \frac{\mathrm{WSD_{act}}}{\mathrm{WSD_{crit}}} \tag{1}$$

RWC compares the water content of a leaf with the maximum water content at full turgor .

$$\mathrm{RWC} = \frac{\mathrm{FW} - \mathrm{DW}}{\mathrm{TW} - \mathrm{DW}} \tag{2}$$

where FW is the field weight, DW the oven dry weight, and TW the turgid weight. Limitations of retrieving RWC using reflectance in the optical domain have been discussed by Bowman (1989) and Ripple (1986).

Unlike the vegetation stress indices, RDI and RWC do take into consideration the quantity of water in the plant. However, two different species may have the same RDI or RWC values with different amounts of water in their leaves. For the purpose of assessing burning efficiency and risk of fire occurrence, these indices might not be suitable because they do not provide an absolute measure of plant water content.

2.3. Direct measurement of vegetation water content

Physical-based studies have shown that SWIR (1400–2500 nm) is heavily influenced by the water in plant tissue (Tucker, 1980; Gausman, 1985). In particular, the wavelengths at 1530 and 1720 nm seem to be most appropriate for assessing vegetation water (Fourty & Baret, 1997). Studies using physical or semiempirical methods have used radiative transfer models to simulate the effect of water content on reflectance (e.g. Jacquemoud et al., 1994; Fourty & Baret, 1997; Ustin et al., 1998). Laboratory measurements performed on five different leaf species (Hunt & Rock, 1989) have shown a good relationship between the EWT and a Moisture Stress Index calculated as the ratio between reflectance value measured at 1600 nm and reflectance value measured at 820 nm. Although these studies have clearly indicated the wavelength domain in which leaf reflectance is influenced by water content, it is necessary to investigate in more details the importance of other factors influencing variations in reflectance.

The following studies described in this paper were designed to retrieve with enough precision water content at leaf level and to set a basis for retrieval of vegetation water content at top-of-canopy and top-of-atmosphere levels. In addition, we have explored the potential for retrieving either Fuel Moisture Content (FMC) or EWT, as each of these is used to express vegetation water content.

3. Basis for measuring directly vegetation water content using remote sensing methods

The first step towards establishing an operational technique to retrieve vegetation water content using remote sensing is to clearly identify and demonstrate where the potential lies. The study investigates the first level at which water content influences a radiometric response, i.e. at leaf level. The research uses laboratory measurements, a leaf optical property model (PROSPECT) and a sensitivity analysis to achieve this and to establish the basis for creation of an operational method at higher levels.

3.1. Vegetation water content definitions

In order to quantify directly vegetation water content, the following two definitions are classically used.

7(i) The FMC defined as the ratio between the quantity of water (fresh weight–dry weight) and either the fresh weight (Mbow, 1999) or the dry weight (Burgan, 1996; Chuvieco et al., 1999):

$$\mathrm{FMC} = \frac{\mathrm{FW} - \mathrm{DW}}{\mathrm{FW}\ (\text{or DW})} \times 100\ (\%) \tag{3}$$

where FW is the fresh weight measured in the field and DW the oven dry weight of the same sample.

(ii) The leaf water content per unit leaf area or EWT defined as the ratio between the quantity of water and the area. EWT corresponds to a hypothetical thickness of a single layer of water averaged over the whole leaf area (Danson et al., 1992)

$$\mathrm{EWT} = \frac{\mathrm{FW} - \mathrm{DW}}{A} \quad (\mathrm{g\ cm^{-2}})\ \text{or}\ (\mathrm{cm}) \tag{4}$$

where A is the leaf area.

These two equations provide information on the amount of water present in vegetation. However, they refer to two different quantities. Gond et al. (1999) measured some biophysical parameters (water quantity, leaf area, dry matter) on five different species in a temperate forest. If these measurements are used to compute FMC (water content/fresh weight) and EWT, we obtain the results shown in Table 1 and Fig. 1. Table 1 presents the field measurements for leaf area, fresh matter and dry matter, as well as the computed EWT and FMC values. Fig. 1 presents the evolution of EWT, dry matter, and FMC values during a growing season (1997) for four species. The results show that a unique FMC value (around 60%) may correspond to different EWT values (Table 1). Conversely, a unique EWT value may correspond to different FMC values (Fig. 1). These examples show that EWT and FMC are two different ways to define vegetation water content and that they are not directly related. In two of the species, *Rhododendron* and *Quercus*, there is actually an inverse relationship between EWT and FMC variations. Our study investigates the potential of retrieving both of these measurements via remote sensing methods.

3.2. Sensitivity of SWIR to leaf water content

Laboratory measurements and simulations of the PROSPECT radiative transfer model allowed us to study the effect of some leaf biophysical parameters (water, dry matter, and chlorophyll content) on reflectance values at leaf level.

3.2.1. Laboratory measurements

We used the data of the LOPEX93 experiment (Hosgood et al., 1994) conducted at the Joint Research Centre by the former Advanced Techniques Unit, Space Applications Institute, Ispra, Italy. Approximately 50 species of trees, crops, and plants were collected in the area of Ispra for this experiment. The leaf hemispherical reflectance was measured with a laboratory spectrophotometer over the 500–2500 nm range in 1 nm intervals. Data on leaf pigments, water content, and biochemical components were also available.

The first step was to investigate the potential of the SWIR over the 1500–1700 nm range for retrieving vegetation water content expressed both in FMC (Eq. (3)) and EWT (Eq. (4)). We selected one set of species with the same quantity of water expressed in FMC and another set of species with the same quantity of water expressed in EWT. Fig. 2a shows the reflectance spectra of four species (*Acer pseudoplatanus* L., *Armeniaca vulgaris* Lam., *Morus alba* L., *Prunus laurocerasus* L.) with similar FMC values (Table 2). Fig. 2b shows the reflectance spectra of three species (*Musa ensete* J.F. Gmelin, *Ficus carica* L., *Hedera helix* L.) with similar EWT values (Table 3).

Fig. 2a shows that variations of reflectance in the SWIR mirror variations of laboratory measured EWT. In Fig. 2b, variations of laboratory measured FMC do not result in similar variations of reflectance in the SWIR domain. We therefore deduct that variations of reflectance in the SWIR only provide information on the quantity of water per unit area (EWT) and not on the FMC.

To further develop our research, we extracted five reflectance values per species at 1600 nm for a data set of 37 species having an EWT ranging from 0.0002 to 0.0524 g cm $^{-2}$. These reflectances have been plotted as a function of EWT in Fig. 3. Results show a logarithmic relationship between EWT and reflectance. This implies that when EWT is high, reflectance values are less sensitive to EWT variations but when the EWT decreases, reflectance values become more sensitive to EWT variations. Thus, it is

Table 1
Field measurements performed by Gond et al. (1999) at leaf level on four species in a temperate forest (Brasschaat, Belgium)

Species	Leaf area (cm^2)	Fresh matter (g)	Dry matter (g)	Water (g)	EWT (g cm $^{-2}$)	FMC (%)
R. ponticum	25.8	0.884	0.342	0.542	0.021	61.31
Q. robur	26.9	0.583	0.233	0.350	0.013	60.03
Mol. caerulea	16.7	0.229	0.096	0.133	0.008	58.07
Pi. sylvestris	0.51	0.040	0.016	0.024	0.047	60.00

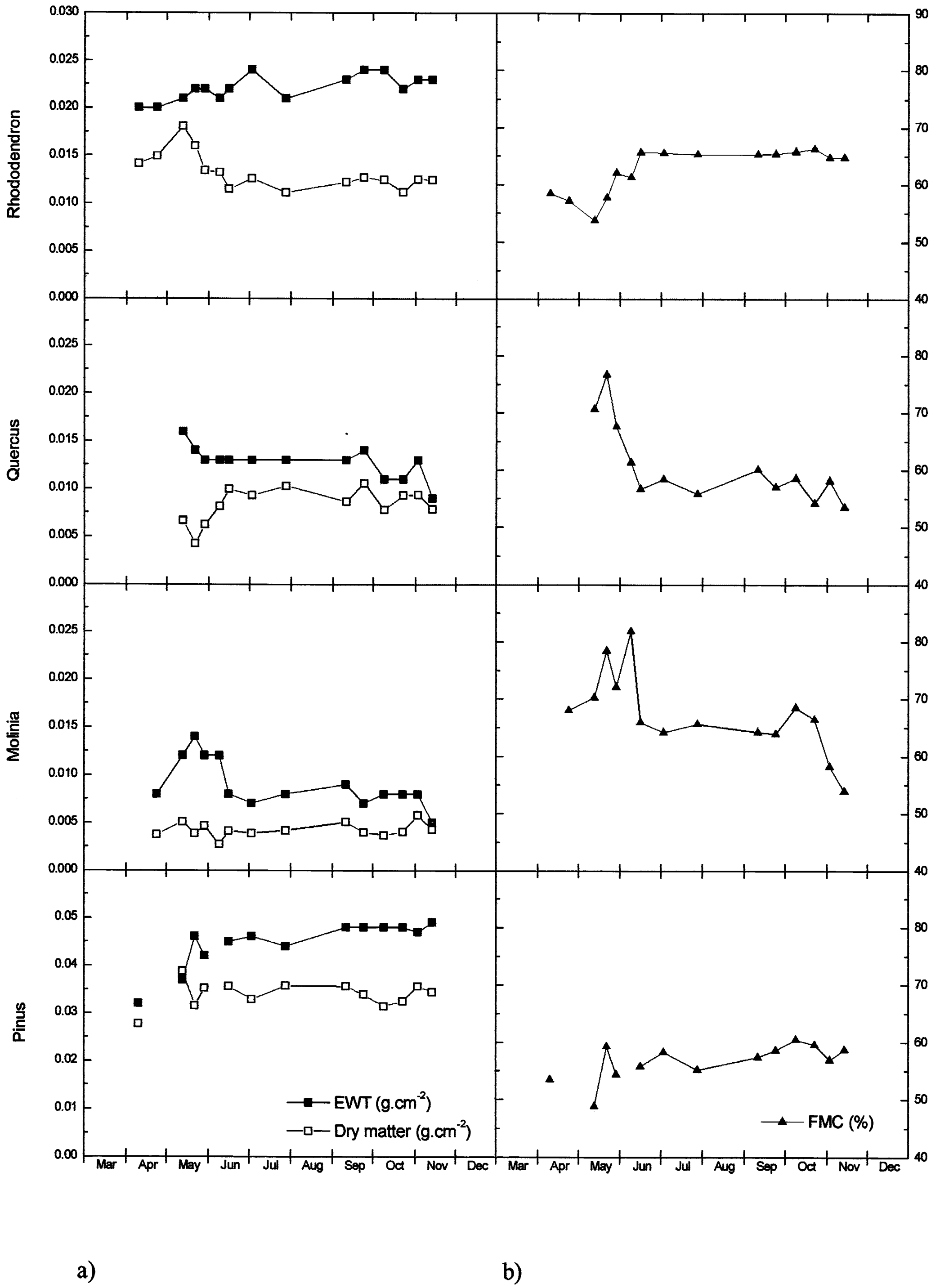


Fig. 1. Evolution of (a) EWT and dry matter during 1997 (after Gond et al., 1999); (b) FMC for the same period.

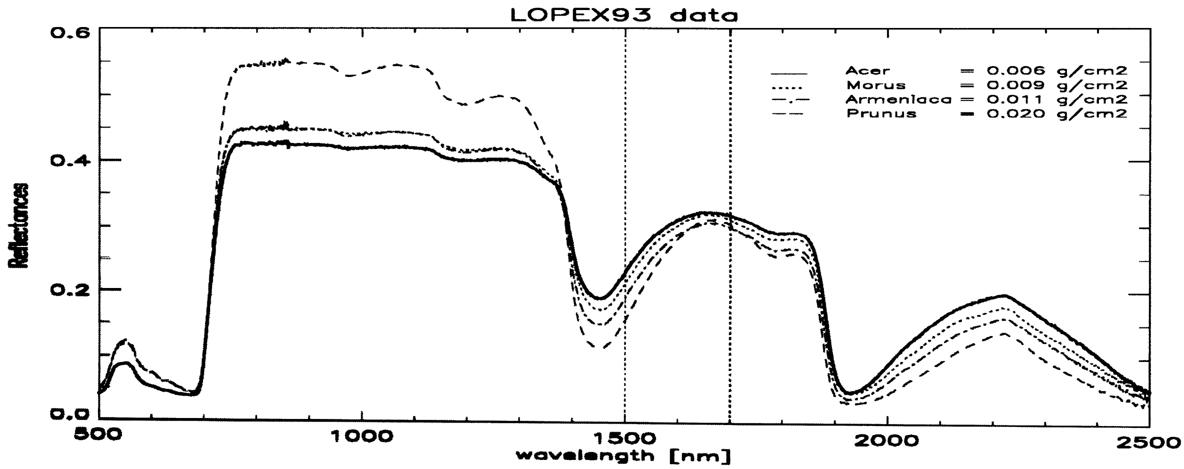
important to note that when vegetation is losing water, variations in reflectance will increase. Using the data set of 37 species, the regression equation relating SWIR reflectance values and EWT is:

$$y = 0.32 + \frac{0.35}{1 + 1615x} - 2.411x \tag{5}$$

$r^2 = .773$

P value $< .001$

where y is the SWIR reflectance value, x the EWT, r^2 is the percentage variation explained by the regression and P value is the significance level.



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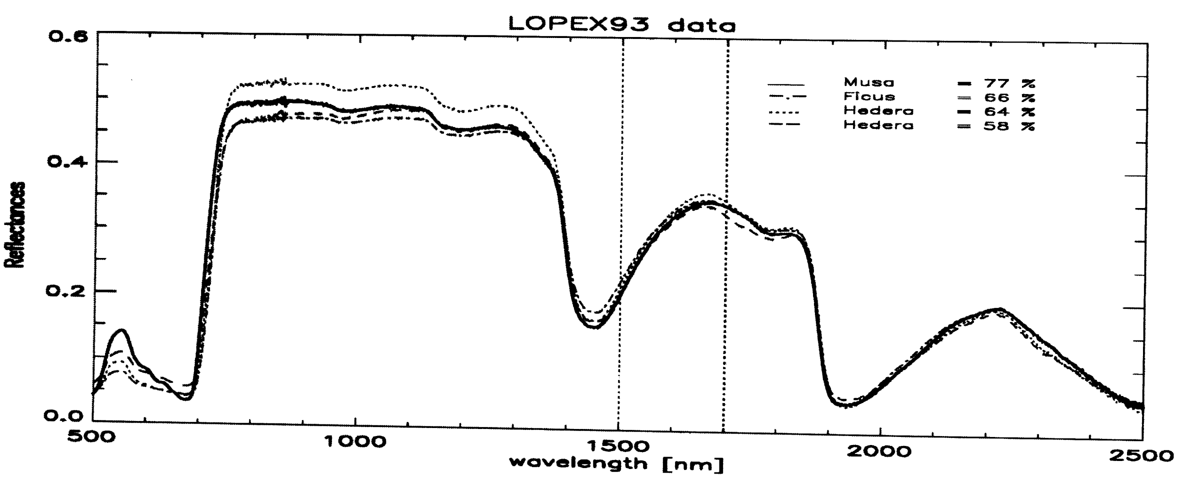


b)

Fig. 2. Leaf reflectance spectra measured in the laboratory (LOPEX93 data) for (a) four different species having a same FMC (65%) value corresponding to four different EWT (g cm^{-2}) values; (b) three different species having a same EWT (0.012 g cm^{-2}) value corresponding to four different FMC (%) values.

Our results also show that for a same EWT, there is some variation in reflectance values. We suspect this variation is due to other factors. To study the importance of the different factors influencing reflectance values, we used the PROSPECT model with a larger data set to simulate the effect of variation in biophysical parameters on reflectance values.

3.2.2. Radiative transfer model

The radiative transfer model PROSPECT (Jacquemoud & Baret, 1990) describes a leaf as a pile of elementary plates composed of absorbing and diffusing constituents. The latest version of this model (Jacquemoud et al., 2000), as used in this study, is a function of the chlorophyll $a+b$ concentration (C_{a+b}), the EWT (C_w), the dry matter content (C_m), and the internal structure parameter (N). With the exception of N, all parameters can be physically measured on the leaf. There have been several approaches proposed for quantifying the parameter N. Jacquemoud & Baret

Table 2
Laboratory measurements on four leaf species

Species	FMC (%)	EWT (g cm^{-2})
Ac. pseudoplatanus	65.05	0.006
Ar. vulgaris	65.18	0.011
Mor. alba	65.20	0.009
Pr. laurocerasus	65.31	0.020

Table 3
Laboratory measurements on four leaf species

Species	FMC (%)	EWT (g cm^{-2})
Mus. ensete	76.61	0.012
F. carica	65.77	0.012
H. helix	63.78	0.012
H. helix	57.99	0.012

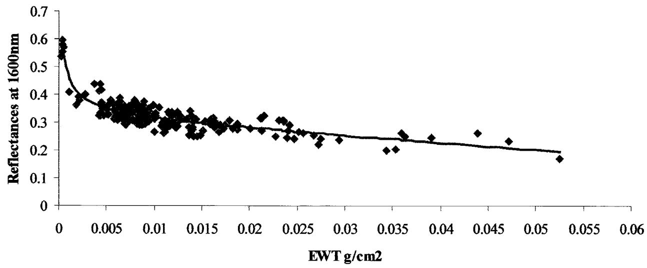


Fig. 3. Reflectance values at 1600 nm, for 37 different leaf species with five measurements per species (LOPEX93 data).

(1990) proposed a hyperbolic relationship between N and the specific leaf area (SLA):

$$N = \frac{0.9\mathrm{SLA} + 0.025}{\mathrm{SLA} - 0.1} \tag{6}$$

where N is the leaf internal structure and SLA is the leaf area per unit leaf dry weight. Veroustraete and Gond (personal communication) proposed another relationship:

$$N = \sqrt[4]{\left(\frac{1}{\mathrm{SLA} - 0.1}\right)} \tag{7}$$

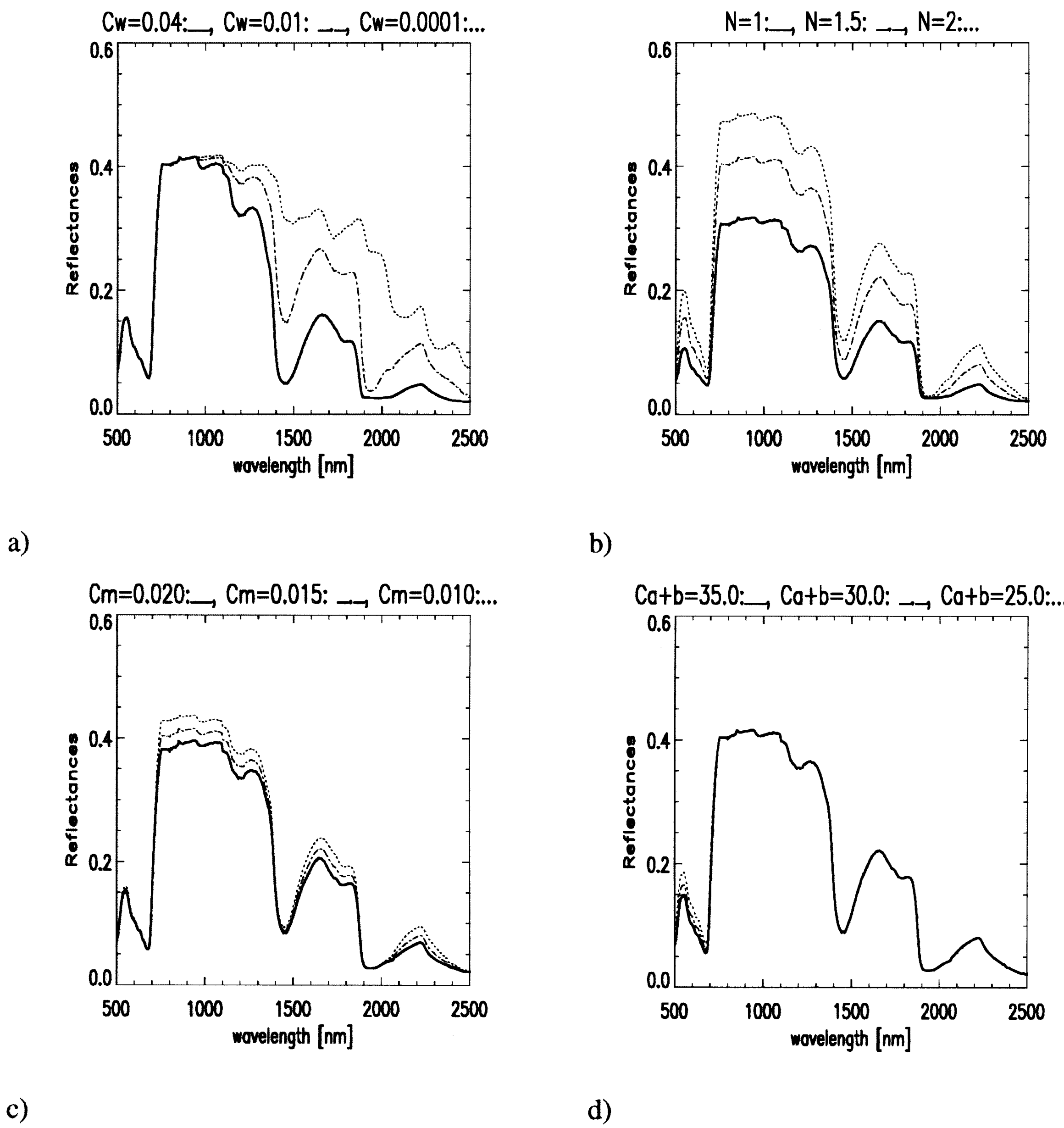


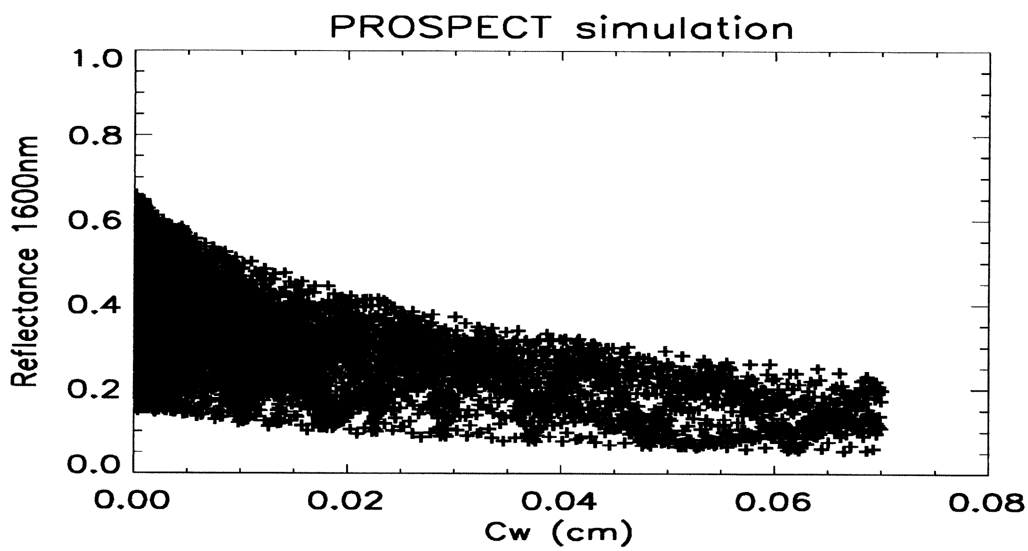
Fig. 4. Sensitivity of leaf spectral reflectance to leaf characteristics. Variations around a "standard" leaf (C_{a+b} = 33.0 μg cm^{-2}, N = 1.5, C_w = 0.020 cm, C_m = 0.015 g cm^{-2}) are considered: (a) with the leaf equivalent water thickness (C_w = 0.04, 0.01, 0.0001 cm); (b) with the leaf internal structure parameter (N = 1.0, 1.5, 2.0); (c) with the leaf dry matter content (C_m = 0.020, 0.015, 0.010 g cm^{-2}); (d) with the leaf chlorophyll content (C_{a+b} = 35.0, 30.0, 25.0 μg cm^{-2}).

Table 4
Range of variations for PROSPECT model

Parameters	Meaning	Unit	Range of variation
C_w	Leaf equivalent water thickness	cm	[0.0001–0.07]
N	Leaf internal structure	–	[1–4]
C_m	Leaf dry matter content	g cm^{-2}	[0.002–0.040]
C_{a+b}	Leaf chlorophyll $a+b$ content	μg cm^{-2}	33.0

However, using these relationships to calculate N for the LOPEX93 data set led to unrealistic results, probably because the relationships were established over limited data sets. For example, when the leaves have a SLA lower than 0.1, N becomes negative using Eq. (6), and Eq. (7) becomes unsolvable. Adjusting the coefficients of Eqs. (6) and (7) could provide more realistic N values for the LOPEX93 data set, but the relationship between SLA and N would remain based on empirical rather than physical methods. Research is still required to measure physically the parameter N. Until this is available, we decided to use a reasonable range for the parameter N. We ran the PROSPECT model with different values of N until the reflectance spectra simulated at 1600 nm fit those measured in LOPEX93. For N ranging from 1 to 4, we obtained the same range of values as in LOPEX93. We thus decided to run PROSPECT simulations using several values of N between 1 and 4.

Simulation of reflectance spectra with PROSPECT was performed in two steps. We first studied the impact of each



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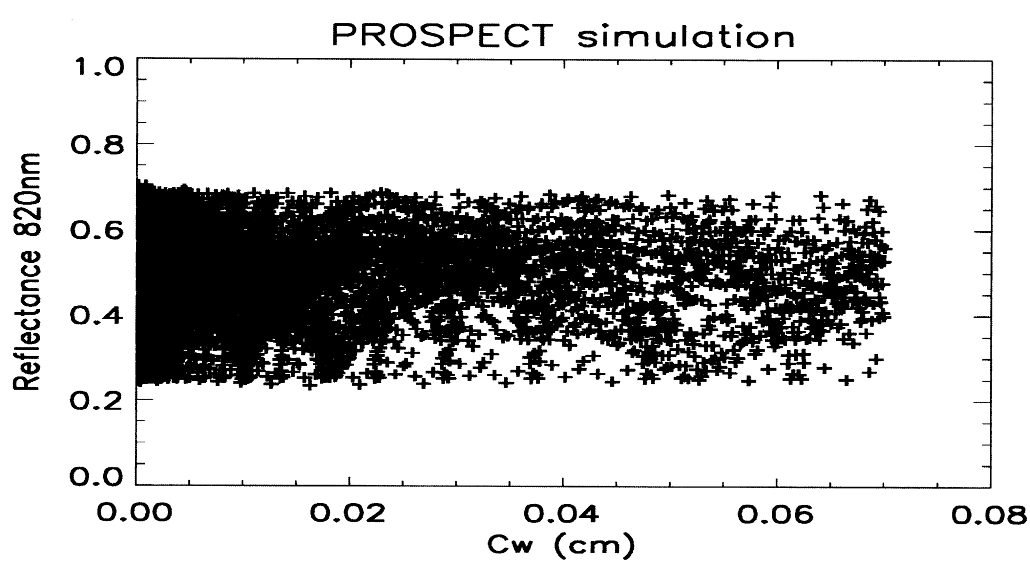

b)

Fig. 5. PROSPECT simulation: (a) in the SWIR (1600 nm), (b) in the NIR (820 nm).

Table 5
Sensitivity analysis: first-order indices

Parameters	Reflectance values at 1600 nm (%)	Reflectance values at 820 nm (%)	Ratio (1600/820 nm) (%)
C_w	35.0	0.0	83.6
N	39.5	74.4	5.6
C_m	21.6	25.6	7.2
Interactions	3.9	0.0	3.6

parameter on the reflectance. We simulated reflectance spectra by varying one parameter at a time, each time keeping the other three parameters stable. Fig. 4 shows that C_w affects the wavelength range from 900 to 2500 nm, N and C_m the entire wavelength range between 700 and 2500 nm, and C_{a+b} only the wavelength range between 500 and 700 nm. The SWIR domain (1500–1700 nm) is therefore affected by C_w, N, and C_m. However, the NIR domain (700–900 nm) is only sensitive to N and C_m. To quantify the effect of these parameters on the reflectance, we performed a sensitivity analysis for the three parameters influencing the SWIR.

We performed a sensitivity analysis using the Extended Fourier Amplitude Sensitivity Test (EFAST) (Saltelli et al., 1999). EFAST allows the computation of the total contribution of each input factor to the output's variance. We input a range of values for C_w, N, and C_m, and EFAST tested the sensitivity of each parameter by suitably selecting combinations of parameter values within the defined ranges. To define the input range for C_w and C_m, we used the minimum and maximum measurements for the leaves collected during LOPEX93 (Table 4). To define the input range for N, we selected 1 through 4 for the above-mentioned reasons. C_{a+b} was kept constant since it has no effect on the SWIR and NIR domains, as seen earlier. Specific distributions were selected for the input parameters: logarithmic for C_w, linear for N and C_m, within the ranges defined above, leading to an input sample of 9987 combinations. We ran PROSPECT for each combination and obtained a set of reflectance values at 1600 nm (SWIR) (Fig. 5a) and 820 nm (NIR) (Fig. 5b). These values were then analyzed with EFAST.

EFAST provides two sets of indices: first-order and total indices. The first-order indices give the additive effect of the corresponding parameters (Table 5). The total indices are overall measures of importance and, as such, take into account the effects of the interactions of each parameter with the other ones (Table 6). In our case, the first-order indices show that the sum of the first-order indices (C_w, N, C_m) equals 96.1% at 1600 nm. This means that in the PROSPECT model, uncertainty in the output is not driven by interaction among the parameters, but that the induced variation is quite additive. It also means that 96.1% of the uncertainty in the model output is explained by the three parameters independently. The remaining 3.9% are explained by interactions between the parameters. For reflectance values at 820 nm, the sum of the first-order indices is equal to 100%, which means that there is no interaction between the parameters.

For reflectance values at 1600 nm, the total indices show that N has the greatest influence (41.1%), and that C_w and C_m account, respectively, for 36.4% and 22.5% in the uncertainty of the output. At 820 nm, the total indices show that N has the greatest influence (74.4%), and that C_m accounts for the remaining 25.6% in the uncertainty of the output; C_w has no effect on output uncertainty.

3.3. Approach to retrieve leaf EWT from spectral reflectances

As demonstrated above, C_w (EWT) is not the only parameter responsible for significant reflectance variations within the SWIR range. Consequently, SWIR reflectance value alone is not suitable for retrieving vegetation water content at leaf level, and additional information is required on the variations due to the parameters N and C_m. By combining this information with the one provided by the SWIR, we can extract the variations induced by N and C_m and thus improve the accuracy in retrieving C_w, i.e. the vegetation water content at leaf level (EWT). Reflectance variations in wavelength ranges only affected by N and/or C_m could provide such information. From the optical range studied above, the only wavelength range to meet these criteria is the NIR ranging from 700 to 900 nm.

To illustrate how this combination of ranges is effective, we used LOPEX93 data to improve the accuracy of EWT estimation just by dividing the reflectance values obtained at 1600 nm by those obtained at 820 nm (Eq. (8)).

$$\text{Simple Ratio} = \frac{\rho_{1600}}{\rho_{820}} \tag{8}$$

where ρ_{1600} is the reflectance value at 1600 nm and ρ_{820} is the reflectance value at 820 nm. Results are presented in Fig. 6. Eq. (5) thus becomes (Eq. (9)):

$$y = 0.666 + \frac{1.0052}{1 + 1159x} - 6.976x \tag{9}$$

$r^2 = .919$

P value $< .001$

where y is the SWIR reflectance value, x the EWT, r^2 is the

Table 6
Sensitivity analysis: total indices

Parameters	Reflectance values at 1600 nm (%)	Reflectance values at 820 nm (%)	Ratio (1600/820 nm) (%)
C_w	36.4	0.0	86.7
N	41.1	74.4	5.8
C_m	22.5	25.6	7.5

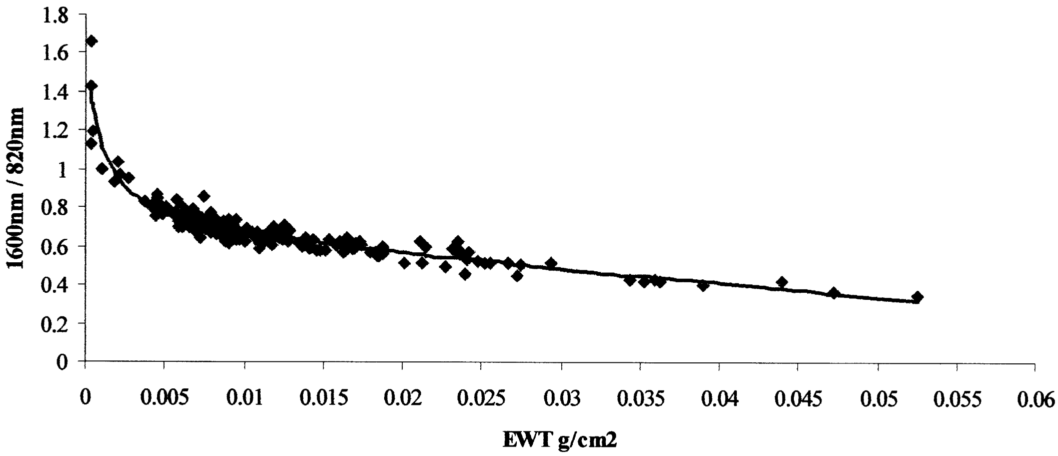

Fig. 6. LOPEX93 data, reflectance values 1600 nm/reflectance values 820 nm.

percentage variation explained by the regression, and P value is the significance level.

An EFAST sensitivity analysis on the Simple Ratio (Eq. (8)) output shows that the C_w parameter accounts for 86.7% of the variation (using the total indices), while N and C_m account only for 5.8% and 7.5% (Table 6). This result confirms the relationship between EWT (for five species) and the Moisture Stress Index (calculated as $R_{1.6}/R_{0.82}$) proposed by Hunt & Rock, (1989).

The Simple Ratio between 1600 and 820 nm could therefore be used as a first approximation to retrieve vegetation water content at leaf level. However, as discussed earlier, the purpose of this research is not to propose an optimized index for retrieving vegetation water content at leaf level but to provide a basis for an operational method to retrieve EWT at top-of-canopy level and top-of-atmosphere. While this study clearly showed that a combination of SWIR and NIR is necessary to improve the accuracy in retrieving EWT at leaf level from optical observations, further research is required to analyze and quantify the scattering effects of other parameters present at canopy and atmosphere levels on the reflectance variations due to C_w, N, and C_m. Research is currently underway using canopy and atmospheric radiative transfer models.

4. Conclusion

This study has shown that information on vegetation water content in terms of EWT at the leaf level can be retrieved from leaf reflectance measurements. It has also established a basis for a more detailed study at top-of-canopy and top-of-atmosphere levels.

Remote sensing using the thermal infrared, the visible and NIR wavelength ranges alone or in established vegetation indices was demonstrated unsuitable for retrieving vegetation water content at the leaf level. These approaches assume that vegetation status and chlorophyll content are proportional to vegetation water content, which is not true for all species. The analysis also demonstrated that remote sensing using the SWIR wavelength range alone is not sufficient in retrieving vegetation water content (in terms of EWT) at the leaf level. Two other leaf parameters (internal structure and dry matter) are also responsible for leaf reflectance variations in the SWIR. A combination of information from both the NIR (only influenced by the internal structure and the dry matter) and SWIR wavelength ranges was clearly demonstrated to be necessary to provide better estimation of vegetation water content in terms of EWT. This combination shows the potential of retrieving vegetation water content at leaf level and sets the basis towards establishing operational techniques for retrieving vegetation water content at top-of-canopy and top-of-atmosphere levels.

Further research is required to understand how this method can be applied at these higher levels. Specifically, we must determine how the leaf parameters (internal structure, EWT, and dry matter) and new parameters (vegetation canopy parameters, illumination and viewing positions, soil parameters) will affect SWIR. This research is underway and will be published at a later date.

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