

Estimating canopy water content from spectroscopy

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Honoring Anatoly Gitelson on the occasion of his 70th birthday

ABSTRACT

Canopy water content is a dynamic quantity that depends on the balance between water losses from transpiration and water uptake from the soil. Absorption of short-wave radiation by water is determined by various frequencies that match overtones of fundamental bending and stretching molecular transitions. Leaf water potential and relative water content are important variables for determining water deficit and drought effects; however, these variables may only be indirectly estimated from leaf and canopy spectral reflectance. We review the state of understanding in remote sensing measurements of leaf equivalent water thickness and canopy water content. Indexes using different combinations of spectral bands estimate leaf and canopy water contents, albeit sometimes with large errors caused by differences in canopy structure and soil surface reflectance. Inversion of leaf and canopy radiative transfer models, such as PROSPECT and SAIL, or learning algorithms, like artificial neural networks and genetic algorithms trained on radiative transfer models, are promising methods for creating global datasets of canopy water content.

Keywords: water absorption features, spectral features, imaging spectroscopy, spectral indexes, radiative transfer models

INTRODUCTION

Water is the dominant component of live biomass (on average 80–95% of the fresh mass of herbaceous material and 50% of the dry mass of woody stems; Larcher, 1975). Plant–water relations determine many fundamental plant processes (Chapin et al., 2002; Asbjornsen et al., 2011), such as transport of nutrients and metabolites within the plant, turgor driven cell expansion, temperature regulation, and energy balance. Foliar water content and leaf water potential (ψ ; Table 1) limit transpiration and carbon gain through stomatal regulation, creating close linkages between the carbon, water, energy, and nitrogen cycles (Waring and Landsberg, 2011). Correctly

describing these linkages is crucial to monitoring and predicting changes in the earth system, understanding feedbacks to atmospheric concentrations of greenhouse gases, and estimating primary productivity of the biosphere (Chapin et al., 2002). Therefore, determination of canopy water content (CWC; Table 1) has important implications for biogeochemical cycling in agriculture, forestry, and natural ecosystems (Gao and Goetz, 1995). Understanding the state of plant water status is essential for assessing drought in natural vegetation (Peñuelas et al., 1993), determining over- and under-watering prac-

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Table 1
Quantities to express amount of water in foliage

Term	Abbreviation or symbol	Formula	Units
Leaf water content *	LWC	$(W_f - W_d)/A_{\text{leaf}}$	kg m^{-2}
Canopy water content*	CWC	$(W_f - W_d)/A_{\text{ground}}$	kg m^{-2}
Equivalent water thickness*	L or C EWT	LWC or CWC	1 mm EWT = 1 kg m^{-2}
Relative water content	RWC	$(W_f - W_d)/(W_{ft} - W_d)$ = LWC/LWC at full turgor	Dimensionless
Leaf water potential	Ψ	MPa or J m^{-3}	
Fuel moisture content	FMC	$(W_f - W_d)/W_d$	dimensionless
Variables	Description	Units	
A _{ground} , A _{leaf}	Area: ground and leaf	m^2	
W _f , W _d , W _{ft}	Weight: fresh, dry, and fully turgid	kg	

*LWC and CWC are also known as the leaf and canopy equivalent water thickness ($1 \text{ mm} = 1 \text{ kg m}^{-2}$). LWC at full turgor = $(W_f - W_d)/A_{\text{leaf}}$. Full turgor : RWC = 100% and $\Psi = 0 \text{ MPa}$

tices in agricultural crops (Moran et al., 1989; Peñuelas et al., 1993, 1997; Shibayama et al., 1993; Peñuelas and Inoue, 1999), assessing forest health (Vogelmann and Rock, 1989; Collins and Woodcock, 1996; Royle and Lathrop, 1997; Allen and Kupfer, 2000; Kasischke et al., 2004; Pontius et al., 2005) and predicting susceptibility to wildfire (Chandler et al., 1983; Pyne et al., 1996; Ustin et al., 1998a; Roberts et al., 2003; Chuvieco et al., 2004; Riaño et al., 2005).

Foliar water content is a highly dynamic component of the plant canopy relative to structural and other biochemical changes, responding quickly to heterogeneity in timing and quantity of precipitation and associated soil moisture. Depletion of foliar water content is of particular importance during drought, when extreme plant water stress produces xylem cavitation (Pockman and Sperry, 2000) that can lead to plant mortality, sometimes at landscape scales (Allen and Breshears, 1998).

Traditional methods for measuring water stress in vegetation rely on direct field sampling of Leaf and Canopy Water Content (LWC, CWC), Relative Water Content (RWC), and leaf (or stem) water potential (Ψ), as defined in Table 1 (see Turner, 1981, for review). Transpiration is estimated from stem water transport or extrapolated from potential evapotranspiration and water availability estimated from weather station data. Field methods are costly and slow and cannot be applied to regional areas or even small watersheds except in the most general assessments. Furthermore, weather stations are so sparsely placed as to generally prevent spatial interpolation outside of major agricultural areas. Because of the sampling limitations, such methods cannot provide long-

term routine monitoring of seasonal and interannual patterns of plant water status. Climatological droughts have plagued every continent in recent years (Dai et al., 2004) and demonstrate the scale of the measurement problem and the need for long-term monitoring.

While in recent years a combination of land cover mapping, point-based biometeorological measurements (e.g., the global network of flux towers), atmospheric soundings, airborne flux measurements, and similar studies have greatly improved our understanding of the fine scale dynamics and heterogeneity in global carbon, water, and nitrogen cycles and their interdependences, a way to spatially scale water dynamics is still needed. Even at the network of flux tower sites, vegetation water content is not sampled systematically. Most ecosystem models today (Foley et al., 1998; Potter et al., 1999) only use remotely sensed vegetation indexes like the normalized difference vegetation index (NDVI; Table 2), to aid estimates of gas exchange (carbon assimilation and transpiration).

Greater use of remote sensing data in addition to vegetation indexes is needed to constrain today's climate and ecosystem models and improve prognostic realism. It is generally agreed that many ecological processes (e.g., respiration, transpiration, photosynthetic regulation) included in these models are not accurately depicted by vegetation indexes and new observational capabilities are needed at better spatial and spectral scales to reduce uncertainty (Ustin et al., 2004; NRC, 2007). Over the past 30 years, a number of new spectral indexes and radiative transfer methods have been developed for non-pigment absorption features, such as the CWC, which could significantly improve ecosystem predictions by

Table 2

Spectral indexes related to leaf and canopy water content. Landsat wavelengths at band centers are indicated; bandwidths are not shown

Index	Abbreviation	Equation	Author	Comments
Normalized difference infrared index	NDII	$(R850 - R1600) / (R850 + R1600)$	Hardisky et al., 1983	Also called the leaf (LSWI) and shortwave infrared water stress index (SISWI)
Moisture stress index	MSI	$R1600/R850$	Hunt and Rock, 1989	
Normalized difference water index	NDWI	$(R850 - R1240) / (R850 + R1240)$	Gao, 1996	
Water Index	WI	$R900/R970$	Peñuelas et al., 1997	
Leaf water stress index	LWSI	$-\log(R1600 - R850) / -\log(R1600 - R850)$	Hunt et al., 1987	R1600ft is the reflectance for a leaf at full turgor (RWC = 100% and $\Psi = 0$ MPa)
Normalized difference vegetation index	NDVI	$(R850 - R670) / (R850 + R670)$	Rouse et al., 1974	Also see Tucker, 1979

better constraint on physiological processes if included in next generation land-surface models. For example, three of the major ecosystem models, Carnegie-Ames-Stanford Approach (CASA) 3-dimensional ecosystem model (CASA-3D), Simple Biosphere model (SiB3), and Ecosystem Demography model (ED2), use NDVI for vegetation greenness, Leaf Area Index (LAI), and fraction of Photosynthetically Active Radiation (fPAR), with all other vegetation inputs prescribed. Understanding physiological mechanisms requires separating leaf area from physiological activity, not possible with NDVI and similar vegetation indexes. Clearly there are opportunities to use spectral information in other bands to improve these models. We review the development of remotely sensed spectroscopy to estimate CWC, an early indicator of drought stress. The spectral absorption properties of pure water can be measured by narrow band sensors in the near-infrared and SWIR regions, although the application of spectroscopy to observe and quantify water content and/or drought stress is complicated by the biological, physical, and observational problems found in vegetation canopies. Consequently, most remote sensing vegetation research today has focused on detection of plant pigments; nonetheless, there have been significant advances in understanding spectral properties in the reflected solar infrared in the past decade, although more remains to be done. Because pigments and water absorption features occur in different wavelength regions (visible vs. infrared), together these measurements provide independent information about

the physiological status of the canopy. Thus, capturing this information could advance ecosystems models by providing independent evidence about plant stress.

OBSERVATIONAL HERITAGE FOR SPECTROSCOPY OF CANOPY WATER CONTENT

The fundamental pure liquid water absorptions at 2870, 2900, 3110, 6080, 1500, and 2500 nm (Goetz, 1992; <http://www.lsbu.ac.uk/water/vibrat.html>) are mostly outside the optical range. Curcio and Petty (1951), Tucker and Garratt (1977), Palmer and Williams (1974), and Kou et al. (1993) established wavelengths for water absorptions within the solar spectrum, between 700 and 2500 nm centered at 760, 970, 1190, 1450, and 1940 nm, and a weaker band that occurs at 850 nm. Carter (1991) later modified these wavelengths for water absorptions at 980, 1240, and 2500 nm.

The vibration of water vapor molecules occurs at 2660, 2740, and 6270 nm (Goetz, 1992; <http://www.lsbu.ac.uk/water/vibrat.html>). The atmospheric water vapor absorptions result from the molecular vibrational and stretching modes: ν_1 (H–O–H symmetric stretch mode transition), ν_2 (H–O–H bending mode transition), and ν_3 (H–O–H asymmetric stretch mode transition). The water absorption feature at 970 nm is attributed to a $2\nu_1 + \nu_3$ combination, at 1190 nm to a $\nu_1 + \nu_2 + \nu_3$ combination, at 1450 nm to a $\nu_1 + \nu_3$ combination, and at 1900 nm to a $\nu_2 + \nu_3$ combination. Tempera-

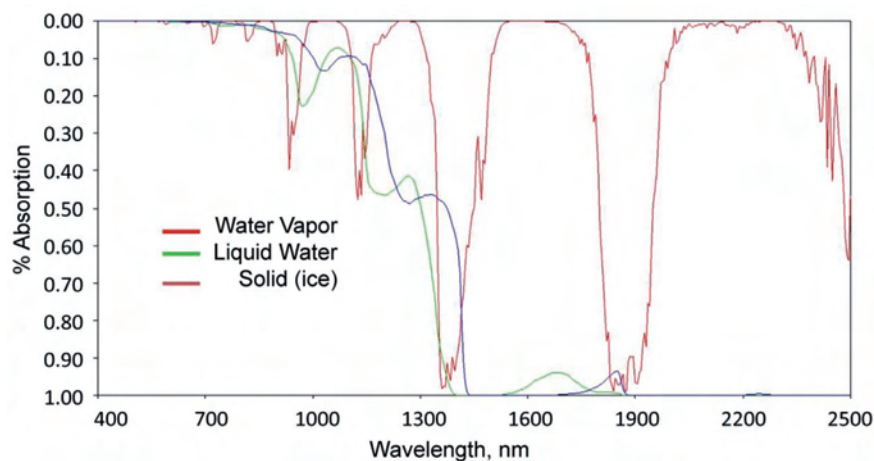


Fig. 1. Narrow band spectroscopy can distinguish the phases of water by wavelength and the concentration by the depth of the absorption of water in vapor, liquid, and solid phases in the solar reflected spectrum. Wavelengths near 900–1100, 1200–1400, and 1300–1900 nm show that absorption spectra for the three phases of water overlap but maxima are displaced in wavelength by about 34, 67, and 130 nm, respectively. Data provided by Robert O. Green, Jet Propulsion Laboratory.

ture affects the harmonics of the O–H bond stretching frequency (Collins, 1925; Dorsey, 1940; Luck, 1963; Tam and Patel, 1979) with temperatures between 0 and 95 °C causing shifts to shorter wavelengths of 20–45 nm, depending on wavelength. Curcio and Petty (1951) noted the shift in absorption position for different states of water, that is, between water vapor, liquid water, and ice, as shown in more recent measurements by Robert O. Green, Jet Propulsion Laboratory (Fig. 1).

Leaf reflectance

In contrast to absorption by photosynthetic pigments in the visible spectrum, water absorption has dominant impacts on reflectance and transmittance of green leaves in the near-infrared (NIR) and shortwave-infrared (SWIR) regions (Gates et al., 1965; Knipling, 1970). Both excess and deficiency of water affect leaf reflectance. Knipling (1970) showed that NIR (700–1400 nm) reflectance declines significantly when leaf cells are saturated with water. This result demonstrated the importance of multiple scattering within the leaf's air cavities, observed by earlier work on leaf optics (Willstätter and Stoll, 1913). Knipling (1970) also described the impact of leaf dehydration and senescence on reflectance: reflectance increases broadly across the wavelength interval from 1600 to 2500 nm.

Direct physiological measurements of leaf water content often rely on leaf relative water content (RWC; Table 1) due to its sensitivity to change. RWC shows a non-linear relationship to leaf water potential (ψ), a measure of the energy required to extract water from

the soil and transport it to the leaf surface. This measure is considered by plant physiologists to provide a good indication of the water deficit (drought) that a leaf is experiencing. ψ is widely used to quantify the response of plants to drought and is inversely related to RWC. Carter (1991) expanded on the work of Knipling (1970) with a detailed examination of wavelength-dependent response to varying RWC, measured by the reflectance difference between the leaf at RWC = 100% and at varying levels of dehydration. Sensitivity varied with leaf anatomical type but for sensitive species at low RWC, reflectance increased by as much as 70% at wavelengths of 1420 and 1900 nm. Carter (1993) later identified wavelengths at 1412, 1978, 2004, and 2401 nm to be most sensitive to changes in RWC. However, thicker leaves with greater leaf water content (LWC) do not show much response at these wavelengths because of water's large absorption coefficients (Fig. 1). Figure 2 illustrates the relationship between spectral reflectance of a corn (*Zea mays*) leaf (medium thickness) and the strength of the specific absorption coefficient for water.

In early field studies of plant water status, Hardisky et al. (1983) were the first to propose and test a normalized difference water index using Landsat TM bands 4 and 5 (see Fig. 3), which they termed the Infrared Index (currently it is referred to as the Normalized Difference Infrared Index (NDII; Table 2)). Hunt et al. (1987) and Hunt and Rock (1989) developed and tested a Leaf Water Stress Index (LWSI; Table 2), which was derived from the Beer–Lambert law to be equal to RWC. However, Hunt and Rock (1989) showed that the LWSI

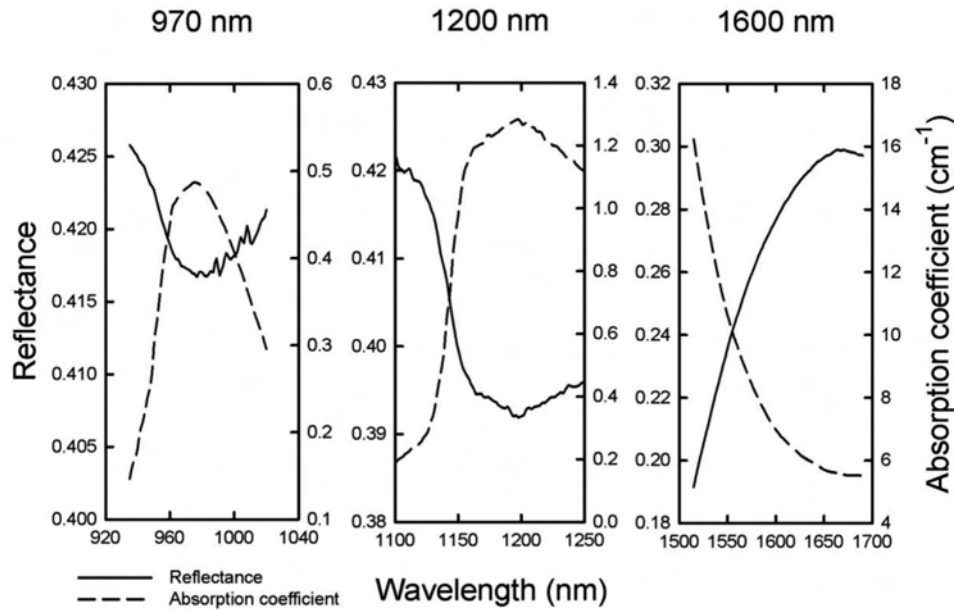


Fig. 2. Spectral reflectance for a fresh leaf of *Zea mays* (left axes, solid lines) and the absorption coefficient for liquid water (right axes, dashed lines) for three wavelength regions: (A) 970 nm, (B) 1200 nm, and (C) 1600 nm.

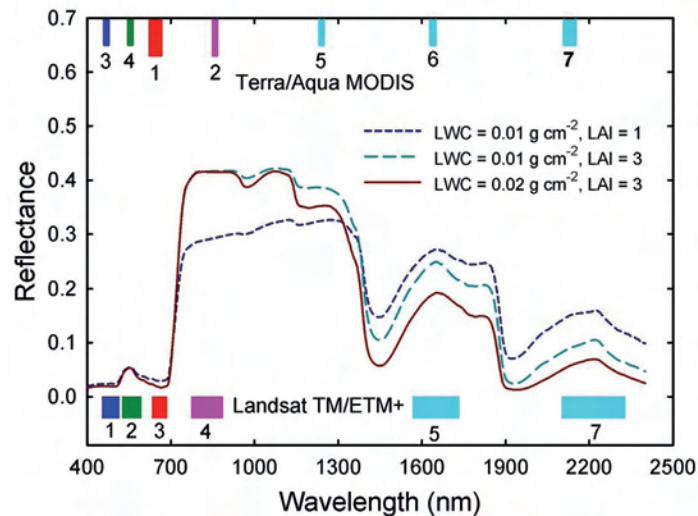


Fig. 3. Vegetation canopy hemispherical reflectance simulations using PROSAIL (Jacquemoud et al., 2009) with MODIS Terra/Aqua and Landsat TM/ETM+ bands identified. Chlorophyll = $50 \mu\text{g}/\text{cm}^2$; Carotenoid = $25 \mu\text{g}/\text{cm}^2$; Brown pigments = 0; Dry matter = $0.01 \text{ g}/\text{cm}^2$; Structure coefficient (N) = 2; Average leaf angle = 50° ; Soil coefficient = 1; Diffuse/direct radiation = 70 %; Hot spot = 0.2; Solar zenith angle = 30° ; Observer zenith angle = 0° ; Azimuth = 0° .

was not practical because of the difficulty in measuring some of the parameters. Furthermore, Hunt and Rock (1989) showed there is a log-linear relationship between the Moisture Stress Index (MSI; Table 2) and LWC for leaves of different species from crops to desert succulents. Cohen (1991a,b) examined Landsat TM band

indexes in laboratory measurements on Coulter pine (*Pinus coulteri*) and lodgepole pine (*Pinus contorta*) needles and showed that MSI was correlated with RWC and ψ . RWC is better related to spectral responses than other ways of quantifying water in vegetation (Ceccato et al., 2002; Sims and Gamon, 2003; Danson and Bow-

yer, 2004), because RWC is defined at the ratio of LWC to LWC at full turgor (Table 1). However, both Cohen (1991a) and Hunt and Rock (1989) expressed reservations about the usefulness of a relative water content index for remote sensing studies because of the need to know both turgid water content and dry weight. More recently Stimson et al. (2005) showed that seasonally induced drought stress in pinyon pine (*Pinus edulis*) and juniper (*Juniperus monosperma*) could be measured with indexes using the 980 and 1200 nm bands, and that these correlated to RWC and ψ . Rodriguez-Pérez et al. (2007) used similar methods on field-based and airborne spectroscopy data for grape foliage and canopies in vineyards to show strong correlations with several measures of water status. The narrow band Photochemical Reflectance Index (PRI) used to estimate Light Use Efficiency (LUE) (Gamon et al., 1992; Garbalsky et al., 2011), has been used to indirectly estimate water stress by monitoring changes in photosynthetic functioning with stomatal closure. Peñuelas et al. (1994) found a correlation between early water stress and low PRI values. Similarly, Sarlikioti et al. (2010) found correlations under high light conditions between PRI and RWC, and Haboudane et al., (2002) reported correlations between PRI and stomatal conductance.

Indexes are useful to assess changes in LWC and CWC from various multispectral sensors such as the Landsat Thematic Mapper. However, indexes are limited by the accuracy of estimated LWC and CWC because differences in leaf morphology and soil background affect reflectance (Yilmaz et al., 2008).

Spectroscopy estimates of leaf water content

The Beer–Lambert Law describes the attenuation of radiation (extinction coefficient, σ_e) transmitted through a homogeneous medium. The extinction coefficient σ_e is the sum of the absorption coefficient σ_a and the scattering coefficient σ_s , which within a plant leaf is predominantly from multiple scattering between air and water interfaces. Assuming this relationship can be used for spectral reflectance from a scattering medium, Downing et al. (1993) proposed that the radiative equivalent water content could be determined. Over a wavelength range (Fig. 2), both reflectance and the absorption coefficient of liquid water vary, so the slope from a linear regression between $\log(\text{reflectance})$ and the absorption coefficient represents the average path length through water in a leaf, i.e., the leaf EWT, which is equivalent to LWC. Furthermore, the intercept of the linear regression is hypothesized to account for fixed effects from errors in the assumptions (Roberts et al., 1998; Sims and Gamon, 2002).

The problem with the analogy to the Beer–Lam-

bert Law is the need to account for multiple scattering within a leaf (Zhang et al., 2011). In Fig. 2, a fresh leaf of *Zea mays* had an LWC of 0.16 kg m^{-2} ; however, regressions of $-\log(R)$ with respect to the absorption coefficient resulted in LWC of 0.61 kg m^{-2} at 970 nm, 0.62 kg m^{-2} at 1200 nm, and 0.43 kg m^{-2} at 1600 nm. Additional terms that account for multiple scattering could be used in regression equations to improve the fit (Zhang et al., 2011); yet added interaction terms do not give an unambiguous estimate of LWC. Nonetheless, the regression equations are useful, because with a good prediction of leaf reflectance based on LWC, the residual between the predicted and measured leaf reflectance shows spectral features related to leaf dry matter content (Gao and Goetz, 1994; Ramoelo et al., 2011; Wang et al., 2011). Thus, spectroscopy estimates are not very useful for directly determining LWC per se; but the regression equations may be used to unmask other spectral features in leaves. A recent paper by Féret et al. (2011) shows how the PROSPECT leaf radiative transfer model can be used to identify wavelengths that will produce improved indexes.

Radiative transfer models

In the 1990s, more sophisticated radiative transfer models began to be developed that accounted for changing leaf biochemistry and structure, including leaf water content (see review by Jacquemoud et al., 2009). The simplest models considered the leaf as a single scattering and absorbing plane-parallel layer (e.g., Allen et al., 1969), while the most complicated models consider the full three-dimensional structure and biochemistry of the cells and tissues that form the leaf (Govaerts et al., 1996; Ustin et al., 2001). At a minimum, physically realistic models require detailed information about the refractive index and the specific absorption coefficients of leaf constituents. Today's models were built on the earlier studies of Allen et al. (1969), who represented a compact leaf as an absorbing plate with rough surfaces producing diffusion. This approach was extended to non-compact leaves by treating them as layers of plates (N) separated by N–1 air spaces (Allen et al., 1970). The widely used and validated PROSPECT model (Leaf Optical Properties Spectra) (Jacquemoud and Baret, 1990) accurately simulates the hemispherical reflectance and transmittance of various types of plant leaves (fresh monocot and dicot leaves, senescent and dry leaves) over the solar spectrum from 400 to 2500 nm (Jacquemoud et al., 2009). After 20 years of use, PROSPECT inputs the concentrations of chlorophyll a+b, carotenoids, EWT, dry matter (DM), and the N structural parameter (the internal structure causing scattering) and predicts leaf reflectance or, inversely, inputs

reflectance and predicts leaf chemistry. It is often linked with one of the SAIL family of models (Verhoef, 1984) as PROSAIL (Jacquemoud et al., 2009) that calculate hemispherical and directional reflectance of an homogeneous vegetation canopy (Fig. 3).

The SAIL model assumes horizontally homogeneous layers and calculates canopy reflectance from input parameters, including the sun/viewing geometry, soil and canopy leaf angles and spectral reflectance, and canopy structure. A “Markov-Chain Canopy Reflectance Model” (MCRM) (Kuusk, 1995a,b) with additions to simulate row crop structure and “Forest Light Interaction Model” (FLIM) (Rosema et al., 1992) address discontinuous canopies and have already been tested theoretically and shown to successfully obtain CWC for crops and forest canopies, respectively (Cheng et al., 2008). “SAIL combined with a geometric model” (GeoSAIL) (Huemmrich, 2001) was also tested in forest canopies (Kötz et al., 2004). A higher level of complexity is introduced in three-dimensional vegetation structure models (Pinty et al., 2004) to understand heterogeneous canopies. For example, the “Forest Light Interaction Model” (FLIGHT) (North, 1996) was successfully applied to estimate CWC (Kötz et al., 2004).

Although these models are closer to reality they require a large number of input variables, making them harder to parameterize (with real data).

Canopy reflectance from narrow band instruments

Figure 3 shows that the band locations for MODIS and Landsat only partially match the location of the main spectral absorption features in plants. Many bands are too wide to effectively measure changes in spectral shape and depth. Given the advantage of contiguous narrow-band spectral coverage in the 400 to 2500 nm region demonstrated in imaging spectroscopy studies, a spectral fitting technique originally designed for improved atmospheric calibration for Advanced Visible Infrared Imaging Spectrometer (AVIRIS) data was developed to simultaneously estimate water vapor and liquid water (Green et al., 1991, 1993; Roberts et al., 1997). Based on the spectral separation between water vapor absorption and liquid water absorption features (Fig. 1), this technique is able to retrieve liquid water over a pixel concurrent with water vapor estimates. The analysis has been applied to airborne imaging spectrometers including AVIRIS (Fig. 4), and to Hyperion data on the EO-1 satellite. Figure 4 shows the simultaneous

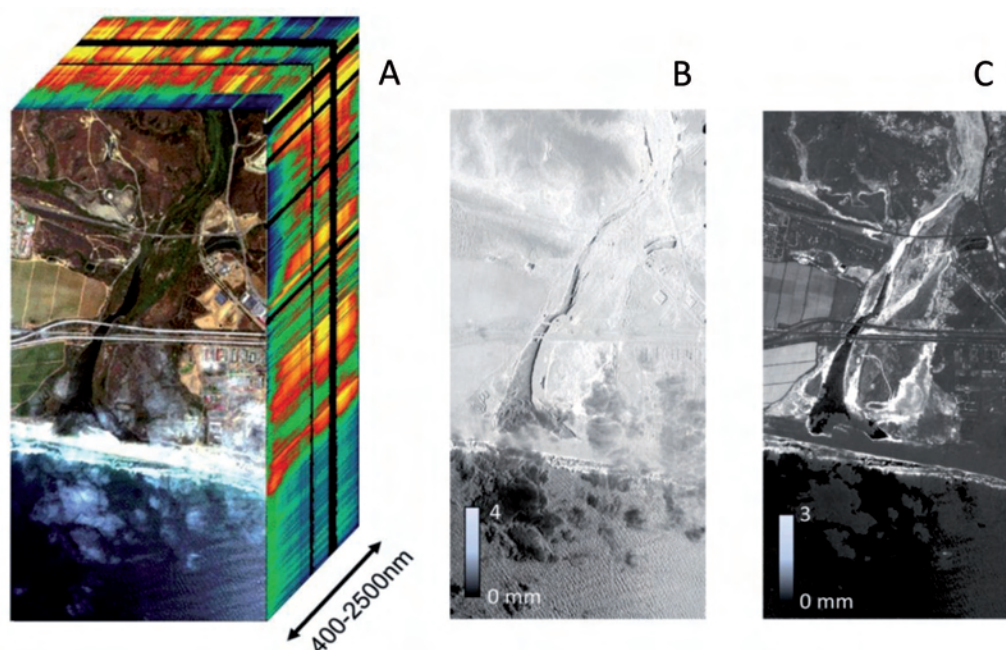


Fig. 4. An AVIRIS data cube (A) shown in true color on the face, was acquired over the lower Santa Margarita watershed, California, at its entrance to the Pacific Ocean, (B) atmospheric water vapor, and (C) canopy water content. Note that over water bodies like the coastal ocean, the algorithm doesn't yield correct values and tonal variation is due to specular reflection from waves and scattering from clouds (seen in 4A). Over land, variations in water vapor patterns are to first approximation due to topography since the atmospheric path length varies with elevation. Terrestrial variation in liquid water concentration occurs where the vegetation canopy is most dense in the riparian zone.

quantification of water vapor and liquid water made by fitting AVIRIS-measured radiance to a radiance spectrum of water vapor and liquid water absorption generated by moderate spectral resolution atmospheric transmittance algorithm (MODTRAN) (Green et al., 1993; Roberts et al., 1997, 1998). This physically based liquid water is expressed as the equivalent water thickness (EWT), which at the leaf level is the volume of water, expressed as depth per unit area. When the area is a pixel, it becomes the equivalent depth of water over the area of a pixel that is required to fit the water absorption modeled in the atmospheric calibration procedure (Green et al., 1991, 1993; Roberts et al., 1997).

Allen et al. (1969) and Gausman et al. (1970) derived the expression for LWC as the thickness of a slab of water that accounts for the radiative properties of a leaf over the 1400–2500 nm range, and validated from measurements on corn and cotton leaves. Narrow-band airborne imaging spectroscopy has been used to quantify EWT and CWC by measuring the depth and area of water absorption features in the 940–1000 nm interval in the reflected NIR spectrum (Green et al., 1991; Gao and Goetz, 1995; Jacquemoud et al., 1995, 1996; Roberts et al., 1997; Zhang et al., 1997; Sanderson et al., 1998; Ustin et al., 1998a; Datt, 1999; Serrano et al., 2000; Cheng et al., 2008).

Subsequent studies have shown the potential for this technique to retrieve EWT, and to use it to monitor vegetation water content (Roberts et al., 1997; Ustin et al., 1998b; Serrano et al., 2000). When applied to images, the leaf EWT multiplied by leaf area index (LAI) yields CWC (Hunt, 1991), as shown in radiative transfer modeling studies (Cheng et al., 2006b). Roberts et al. (1997) used CWC to monitor temporal and spatial variation in water content in herbaceous, shrub, and conifer vegetation. Ustin et al. (1998b) compared different methods for estimating CWC and showed good estimates for chaparral shrubs and detected seasonal differences, although Serrano et al. (2000) later found significant but moderate correlations (0.30–0.41) with index methods, including the simple water index (WI, Table 2), the normalized difference water index (NDWI, Table 2) compared to the method of Green et al. (1991; 1993) and Roberts et al. (1997).

Cheng et al. (2006b) utilized three linked leaf-canopy radiative transfer models to simulate AVIRIS-equivalent spectra using the MODTRAN based code implemented in Atmospheric Correction Now (ACORN) software (ImSpec LLC, <http://www.imspec.com>), in Mode 1.5, for three architecturally different vegetation scenarios. Retrievals of CWC from these synthetic spectra were shown to be sensitive to changes in the EWT (input into the simulation). The major sources of uncertainty

were shown to be from leaf dry matter (DM) and soil background in retrievals of CWC (Daughtry and Hunt, 2008). The potential use of AVIRIS CWC for validating retrievals from MODIS data was also demonstrated at three study sites ranging from crops to woodland and to forest ecosystems (Cheng et al., 2006b).

MODIS, with its morning and afternoon overpasses, provides the required high temporal resolution SWIR bands that are located close to CWC absorptions. Zarco-Tejada et al. (2003) showed that MODIS could estimate CWC from leaf EWT and LAI and that it was possible to accurately follow changes in canopy water content even in low-water-content chaparral shrublands, based on a time series of MODIS data extending over the summer drought (~6 months) in the California Coast Range compared to field-measured fuel moisture content (FMC). This radiative transfer method was further developed by Trombetti et al. (2008) to produce monthly CWC maps for the continental United States.

Modeling canopy water content using a physically based approach

Inversion of radiative transfer models (Jacquemoud and Baret, 1990; Zarco-Tejada et al., 2003; Riaño et al., 2005; Yebra et al., 2008) can be used to account for differences in the types of leaves and canopy structure that are found in different vegetation biomes. These models generally identify the best fit between the model and empirical data, which is evaluated using a merit function. The whole spectrum or only part of a spectrum can be used to establish the best fit merit function (Jacquemoud et al., 1996). Even vegetation indexes have been used for this purpose (Zarco-Tejada et al., 2003). These methods for retrieving water content can be applied to broad scales with different environmental features, but they are computationally very expensive (Fang and Liang, 2003). Methods proposed to solve the computational limitations include using a Look Up Table (LUT) (Schaepman et al., 2005) or applying a machine learning algorithm like an Artificial Neural Network (ANN; Trombetti et al., 2008), Genetic Algorithms (Li et al., 2007), and partial least squares methods (Féret et al., 2011).

ANN models trained from a radiative transfer model (Fig. 5) have been successfully applied to estimate biophysical parameters, such as photosynthetic activity (Baret et al., 2007), gap fraction (fraction of ground area not covered by canopy crowns; Baret et al., 1995), cover fraction and leaf area index (Weiss et al., 2002; Fang and Liang, 2003; Baret et al., 2007), all of which demonstrated good results. These models can be applied to large datasets and produce high accuracy at feasible speeds. An ANN technique was successfully applied to

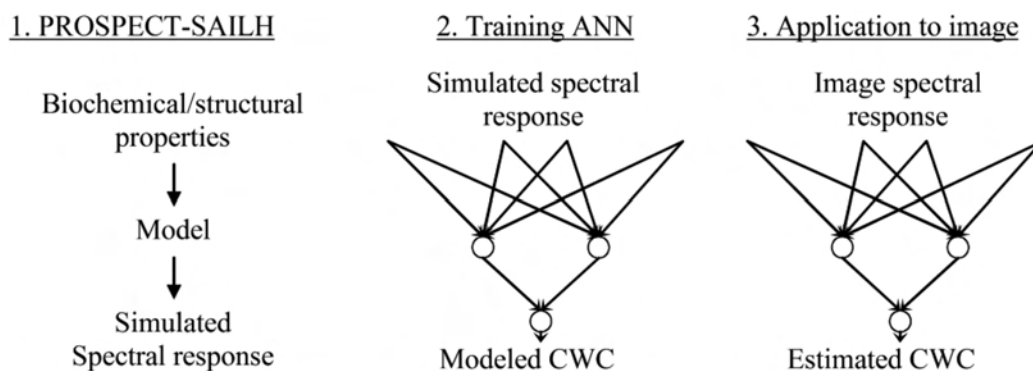


Fig. 5. Sequence of steps followed to generate canopy water content (CWC) in the model developed by Trombetti et al. (2008). In the first step, PROSPECT-SAILH was used to simulate the spectral response to canopy water using real leaf spectral data and associated water contents. In the second step, an artificial neural network was trained and tested using the simulated PROSPECT-SAIL data. In the final step the ANN model is applied to MODIS imagery to measure canopy water content, after it is trained for specific land cover types, using a look up table for cover types.

generate monthly CWC maps from MODIS data for the continental U.S. (Trombetti et al., 2008), which showed realistic changes in water contents given climate patterns and phenological timing. This model is designed for homogeneous canopies, such as grasslands and it behaves differently when applied to more discontinuous and heterogeneous canopies. To account for structural differences Trombetti et al. (2008) developed different calibration equations for different plant functional types based on land cover classification. To obtain realistic results, the range of biochemical/structural properties selected to model the spectral responses must cover the actual range of biochemical and structural values of the land covers represented for the relationships to be valid (Trombetti et al., 2008).

Soil reflectance is one of the most sensitive parameters in canopy reflectance models (Fang and Liang, 2003). Rubio et al. (2006) studied the effect of changing soil reflectance on estimates of CWC by generating two synthetic data sets with the PROSPECT-SAILH model and three soil spectra that ranged from light to dark and showed extreme reflectance values in the 400–2500 nm range, from low to high reflectance. They trained an ANN against data from the Soil Moisture Experiment (SMEX) 2004 and found the choice of soil type had little influence on the model performance, with similar R^2 values around 0.60 in all three cases. However, differences in the root mean squared error (RMSE) were significant. CWC estimates produced by training the ANN with the bright soil dataset (high reflectance) had the lowest RMSE, 0.11, compared to those from medium or dark soil datasets. Cheng et al. (2006a) reported similar behavior in their CWC modeling study.

THE RELATIONSHIP BETWEEN CANOPY WATER CONTENT AND FUEL MOISTURE CONTENT

The highly dynamic component for estimating wildfire danger is live fuel moisture content (FMC; volume of water per unit dry matter of living plants), which varies diurnally and daily during fire-prone dry periods. This indicator of fire danger requires measurement of both CWC and aboveground dry leaf biomass (DM). Current operational methods for estimating FMC require meteorological wildfire danger indices. The Canadian drought code, for example, estimates soil water content in the plant root zone based on multi-temporal meteorological data, which use a limited number of sample points and can be only indirectly related to live vegetation FMC (Camia et al., 1999). MODIS provides the spatial and temporal coverage needed for integrating CWC estimates into FMC to improve wildfire danger and wildfire behavior models.

CWC has been used to quantify the water component of FMC (Ceccato et al., 2002; Sims and Gamon, 2003; Danson and Bowyer, 2004). In a simulation study, Fourty and Baret (1997) showed that CWC was easier to estimate than dry matter (DM) due to the specificity of absorption features for water. CWC can be related to FMC (Zarco-Tejada et al., 2003), if species with similar DM contents are taken into account (Chuvieco et al., 2003; Yebra et al., 2008). Although it is difficult to obtain accurate timely and spatially distributed estimates of DM content with any of today's optical, radar, or lidar satellites, one method proposed by Chuvieco et al. (2003) to obtain annual estimates of spatially

distributed DM content is to make CWC measurements near the end of the driest season since this parameter is limited by variation in foliar biomass. They assume that this biomass estimate will remain relatively constant, i.e., that it does not change rapidly over the following year (or even several years) without a change in land cover (Chuvieco et al., 2003). Dry matter content is then assumed to be constant throughout the year, although a small overall decline during the drought period (Garnier et al., 2001) and a small accumulation during favorable periods of carbon gain are expected. Additionally, dry matter exhibits several absorption features in the reflected SWIR (Jacquemoud et al., 1995, 1996; Asner, 1998; Jacquemoud and Ustin, 2003) which can be measured by optical sensors. Multispectral indexes like the cellulose absorption index ($CAI(nm) = 100[0.5(R_{2031} + R_{2211}) - R_{2101}]$) (Nagler et al., 2000), the ASTER-defined lignin-cellulose absorption index ($LCA = 100[\text{bands } (6 - 5) + (6 - 8)]$ where ASTER band 5 is 2145–2185 nm, band 6 is 2185–2225 nm, and band 8 is 2295–2365 nm (Daughtry et al., 2005), and the improved Shortwave-Infrared Normalized Difference Residue Index [$INDRI = \text{bands } (6 - 7)/(6 + 7)$], with band 7 at 2235–2285 nm have been developed for this purpose and retrievals of DM can be combined with CWC to obtain accurate measurements of FMC.

DISCUSSION

Plant water content is the major factor limiting plant productivity through limiting development, loss of leaf area, or controls on rates of autotrophic respiration. Monitoring of plant water content is critical in determining the dynamic risk of wildfire, among other critical ecosystem processes. Greenness indexes capture the temporal patterns of annual phenology but they miss changes in physiological characteristics that are unrelated to changing leaf area, and most importantly, to dynamic processes related to plant water use and water relations. Today's satellite technologies (Landsat TM, MODIS, ASTER, SPOT, etc.) are primarily limited to measurements of canopy greenness because the bands are not optimized for measurements of CWC, even though relevant water and dry matter indexes have been developed from each sensor. These indexes work well when there is little spectral variation attributable to other materials and the only varying property is the CWC.

Laboratory, field, and airborne spectroscopy data have been shown to measure and quantify water absorption features in the solar spectrum that directly relate to plant physiological conditions, including relative water content and water potential. Data from the new spectroscopy measurements, independent of but simul-

taneous with photosynthetic pigment concentrations, will provide new information about constraints on plant physiological processes that will lead to improved understanding of interactions among global carbon, water, energy, and nitrogen cycles. Spectroscopy uniquely makes multiple spectral feature measurements simultaneously, providing enough spectral dimensions to address the complexity of ecosystems and their non-linear, interacting processes. Uncertainty about vegetation feedbacks to the climate system through these cycles gives rise to the largest uncertainty in predicting climate change (IPCC, 2007). There is also a growing concern that the Earth's freshwater resources will be inadequate to support competing allocations between human needs and natural resources (Vorosmarty et al., 2000; Foley et al., 2005; Oki and Kanae, 2006).

There are still significant problems that must be solved to apply these models with confidence to global spectral datasets. The issues related to measurement of canopy water content today are primarily caused by the lack of a comprehensive global network of validation data sets and spatially explicit knowledge about the spectral variability of soil and plant dry matter, as well as our limited capacity to fully measure or model three-dimensional canopy structure and to include these landscape properties spatially and temporally into canopy models.

The lack of a global validation network can be resolved with a dedicated testing program to determine the extent to which canopy structure affects the remote sensing measurement of water content. Coordinated field measurement programs are best conducted by governmental and other agencies, which have been used in the past to address other observational problems. We anticipate that a family of CWC models will be defined that account for major architecture classes (starting from the most simply defined, by growth form: grass/herb, shrub, forest, possibly with additional sub-classes like conifer vs. broadleaf or evergreen vs. deciduous). Until there is an imaging spectrometer in orbit capable of making systematic global observations to resolve the measurement uncertainty, the potential to use CWC to monitor ecosystem condition and health will remain a research problem. NASA's HypsIRI imaging spectrometer is the only planned satellite with the spectral capability to provide wall-to-wall global coverage at monthly repeat cycles, and its launch has been delayed for at least another decade due to US budget limitations.

Canopy reflectance models are limited today by inadequate spatial and temporal information about the reflectance of soil and plant dry matter/residues. With the high spectral resolution of spectrometers today, it may be possible to better define these properties from

principles of spectroscopy. To invert canopy radiative transfer models it is necessary to correctly input the spectral properties of soils and dry plant residues to retrieve quantitative measures of plant biochemical contents. We know that spectral properties of dry plant matter vary with species and that these properties change with the state of decomposition (e.g., Nagler et al., 2000; Roberts et al., 2004). No theoretical basis has developed to classify the chemistry of these materials, a necessary step if we are to globally extend spectroscopy models. The work by Daughtry, Nagler, and their co-workers on the CAI index is a good start, but this index has been mostly used for herbaceous crop residues in North America and has not been tested against the diversity of global vegetation types or in terms of spectral changes during decomposition. Because of relationships between dry biomass and other ecological questions like carbon sequestration and turnover, there is an urgent need to systematically address this problem. Similarly, there have been few advances on understanding soil spectral properties and generalizing spectral patterns for different soil properties since the work of Stoner and Baumgardner (1981) and Baumgardner et al. (1985).

Our ability to fully measure or model three-dimensional canopy structure has greatly improved in recent years with the rapid expansion of available LiDAR data (Vierling et al., 2011) but analysis remains a bottleneck, particularly for land cover types with multilayer canopies or at least overlapping tree crowns, and further programming effort is needed, combined with better understanding of rules for canopy growth patterns. There is a significant opportunity for synergy in fusing hyperspectral imagery with the three-dimensional structural information derived from Lidar and Radar data (Ustin and Gamon, 2010). Recent studies of tropical forest chemistry and species distributions as shown by G.P. Asner and his colleagues demonstrates the enhanced information that can be extracted using combined data sources. For example, Asner et al., 2010, and Vitousek et al., 2010, use fused LiDAR and imaging spectrometer data to map forest structure and biogeochemistry, and these to map plant species and communities and biological invasions in Hawaii.

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