ESTIMATION OF LEAF WATER CONTENT FROM FAR INFRARED (2.5 -14 µm) SPECTRA USING CONTINUOUS WAVELET ANALYSIS

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ABSTRACT

The objective of this study was to estimate leaf water content based on continuous wavelet analysis from the far infrared (2.5 − 14.0 µm) spectra. The entire dataset comprised of 394 far infrared spectra which were divided into calibration (262 spectra) and validation (132 spectra) subsets. The far infrared (2.5 − 14.0 µm) spectra were first transformed into a wavelet power scalogram, and then linearly plotted against leaf water content. The six individual wavelet features identified in the mid infrared yielded high correlation with leaf water content (R^2 = 0.86 maximum, 0.83 minimum), as well as low RMSE (maximum 8.56%, minimum 9.27%). The combination of four wavelet features produced the most accurate model (R^2 = 0.88, RMSE = 8.00%). The models were consistent in terms of accuracy estimation for both calibration and validation datasets, indicating that leaf water content can be accurately retrieved from mid to thermal infrared electromagnetic radiation.

1. INTRODUCTION

Leaf water content is an important indicator of plant health, vigour and photosynthetic efficiency [1]. Accurate estimation of plant water content plays a crucial role in assessing drought risk [2], predicting wildfire and monitoring the physiological condition of vegetation [3], while in the agriculture domain it helps in scheduling irrigation and estimating crop yields [4]. Conventional methods of estimating leaf water content in the field are time consuming and location specific. Remote sensing is an effective alternative to field sampling for the accurate retrieval of leaf water content, being nondestructive and providing continuous spatial coverage of a large area [4, 5].

Leaf water status has been successfully estimated using the near infrared and shortwave infrared [4, 5]. In contrast, little attention has been paid to the mid and thermal infrared (2.5 – 14 µm) domain because of a number of challenges, including lack of equipment, low signal to noise ratio, and the subtle and complex nature of the spectral features of vegetation [5-7]. However, research in the mid to thermal infrared suggests that the spectral response of plants is dominated by leaf water content and leaf epidermal materials [8-10], although there is no literature relevant to the successful retrieval of leaf water content and water stress indices from multiple species.

This paper investigates the potential of laboratory measured far infrared (2.5 –14.0 µm) Directional Hemispherical Reflectrance (DHR) spectra for the retrieval of leaf water content based on a continous wavelet analysis.

2. MATERIALS AND METHODS

2.1 Leaf water content and spectral measurement

Leaves (6 or 10 leaves per species) were acquired from nine plant species. The leaves, attached to small twigs, were placed in moist cotton in the laboratory to avoid desiccation. Within 30 minutes, spectral measurements were made of the fresh leaves. Different levels of leaf water content were obtained by successively air drying the leaves and taking measurements after every four hours. The leaf water content was precisely measured using a digital weight balance with 100 µg accuracy. Prior to measuring the final (completely dry leaf) water content level, leaves were oven dried at 60^0C for 90 minutes.

The gravimetric leaf water content was estimated using the following equation:

$$LWC_f = 100(Mw - Md)/ Mw \quad (1)$$

where *Mw* represent the wet leaf weight and *Md* is the weight of completely dried leaf (dried in oven for 90 minutes at last succession). LWC_f is the leaf water content relative to wet leaf weight.

The DHR spectra (2.5 – 14 µm) of leaves (at various drying levels) were acquired using a Bruker VERTEX 70 FTIR (Fourier transform infrared; Bruker Optics GmbH, Ettlingen, Germany) spectrometer. The spectral measurement per species varied from 24 to 70, depending on the speed of dehydration and the number of leaves (per species) selected at the initial stage. A total of 394 spectra were measured. Two thirds (n = 262 samples) of the total data were (randomly) used for calibration and one third (n = 132 samples) for validation purposes

2.2. Feature selection using continuous wavelet analysis

To select the wavelet features (i.e. single units in the wavelet scalogram) most sensitive to leaf water content, a four-step procedure was followed. In step 1, the wavelet power (wavelet scalogram) was computed for all spectra using the continuous wavelet transform (CWT) function. The wavelet scalogram is a function of wavelength (µm) and scale. In step 2, a Pearson correlation (R^2) was calculated for leaf water content and the wavelet scalogram in order to identify features sensitive to the variation in leaf water content. Then, all significant ($p < 0.05$) features were sorted in descending order based on R^2, and a threshold (of the top 1%) was applied to identify spectral features highly sensitive to variations in leaf water content. The features demarcated by this threshold were adjacent (consecutive) in scale and wavelength dimension and clustered in a wavelet region sensitive to leaf water content. To avoid multicollinearity of consecutive wavelet features, at step 4 an individual feature with the highest R^2 was selected from each spectral region. The sparsely dispersed individual features (selected at step 4) represent the most sensitive features and were expressed in scale as well as wavelength dimension.

2.3 Statistical analysis

The calibration dataset was used to identify the sensitive wavelet features by using CWT procedure. Simple linear regression was used to model the relationship of individual wavelet features (independent variable) with leaf water content (dependent variable), while stepwise multiple linear regression was used to model the relationship between multiple wavelet features and the leaf water content. The models resulting from the calibration dataset were applied to the validation dataset, and the predictive performance assessed using R^2 and RMSE between the measured and predicted leaf water content.

3. RESULTS

3.1 Features sensitive to leaf water content

The transformation of DHR spectra using continuous wavelet analysis highlighted six spectral features (single feature per spectral region). The correlation scalogram (Table 1) shows regions with high R^2 located in the mid infrared (2.5 – 6 µm), and the positions (wavelength and scale) are shown in (Table 1). The R^2 varied from 0. 87

(feature a, (Table 1)) located at wavelength 3.302 µm, to $R^2 = 0.84$ at wavelength 2.508 µm (feature e, (Table 1)). The combination of the spectral features using stepwise multiple linear regression resulted in a high coefficient of determination (adjusted $R^2 = 0.89$). Stepwise regression produced the highest accuracy model (Table 1) by the inclusion of four wavelet features (a, b, e, d).

Table 1. Summary of the selected wavelet features, the wavelet features, their spectral location, scale, correlation with leaf water content for calibration and validation data, RMSE of predicted versus measured leaf water content, and relation of the selected features to the existing literature.

Feature	Wavelet feature location		Calibration data		Validation data		Features related to
	Wavelength	Scale	R^2 (%)	Stat. Sig	R^2 (%)	RMSE (%)	
a	3.203 µm	7	0.876	$P < 0.01$	0.863	8.56	Water at 3.05 µm
b	3.329 µm	6	0.875	$P < 0.01$	0.862	8.60	
c	3.999 µm	8	0.856	$P < 0.01$	0.849	8.98	Lignin at 4.00 µm
d	2.910 µm	8	0.855	$P < 0.01$	0.841	9.22	Water at 2.91 um
e	3.857 µm	7	0.855	$P < 0.01$	0.841	9.24	Lignin at 4.00 µm
f	2.508 µm	9	0.839	$P < 0.01$	0.831	9.49	Water at 2.50 um
a,b,e,d	Stepwise regression		0.890	$P < 0.01$	0.883	8.00	

3.2 Validation

The models resulting from the calibration dataset were applied to a validation dataset. Among individual wavelet features, the most accurate model ($R^2 = 0.86$, RMSE = 8.56%) was produced at wavelength 3.203 µm and scale 7 (feature a; Table 1). The stepwise regression model based on a calibration dataset estimated the leaf water content with the highest accuracy ($R^2 = 0.88$, RMSE = 8.0%). The validation results (Fig.1) show that data points are dispersed close to the 1:1 line, except for higher leaf water content (above 40 %). The DHR reflectance and wavelet power saturate at higher (above 40%) leaf water content.

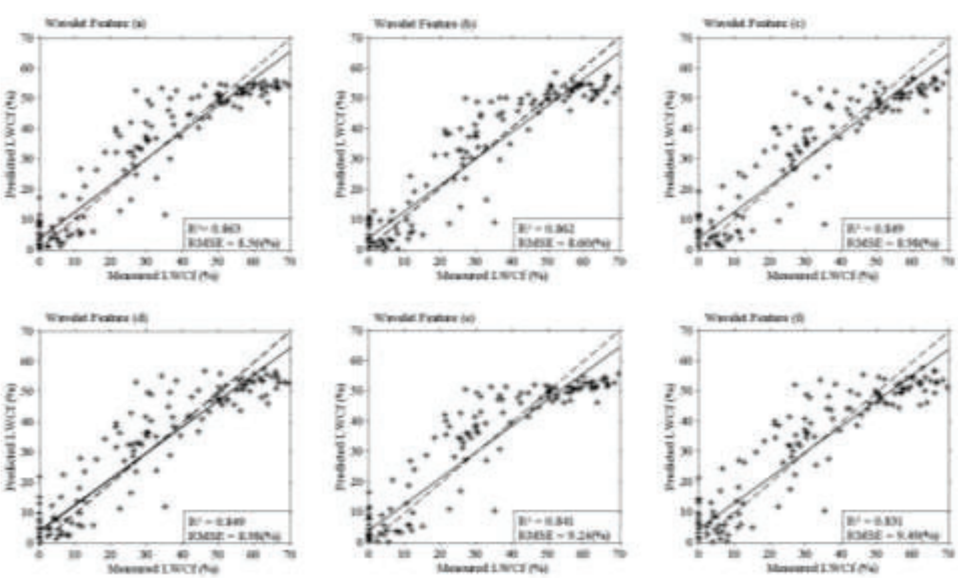

Figure 1. Measured versus predicted LWC_f (%) based on the model developed from individual wavelet features; the highest correlation shown produced using selected wavelet feature at 3.203 µm (scale 7).

4. DISCUSSION

This study quantifies the relationship between DHR spectra (mid to thermal infrared; 2.5 – 14 µm) and leaf water content using continuous wavelet analysis. Retrieving leaf water content using the mid to thermal infrared resulted in a more accurate estimate of leaf water content (R^2 = 0.88) than when using visible to shortwave infrared [11] (R^2 =0.77). In other words, our results complement knowledge from the visible to short wave infrared (0.4 – 2.5 µm) domain that leaf water content relates to remotely sensed spectra [4, 5] and especially that higher explained model variance is obtained using the mid infrared and thermal infrared.

The selected wavelet features that significantly explain foliar water content are located only in the mid infrared, with no features from thermal infrared being selected, thus confirming recent findings by other researchers [9, 12, 13]. The selected wavelet features were spectrally positioned at the edge of the water, cellulose and lignin absorption features. The wavelet features at 2.508 µm (feature f), 2.910 µm (d), 3.203 µm (a), and 3.329µm (b) could be attributed to the absorption bands related to leaf water content [6, 9, 12, 13] . The wavelet features at 3.857 µm and 3.999 µm were at the leading edge of spectral features (i.e. the cellulose and lignin spectral peak at 4.00 µm).

An accurate retrieval of leaf water content was achieved despite the influence of variation in leaf structure from different plant species. The continuous wavelet analysis has proved an effective tool for analyzing DHR spectra (comprising thousands of bands) and selecting spectral features related to leaf water content. The continuous wavelet analysis segregates the water absorption features into various scales. The different scaled features contain information on both narrow and broad absorption features related to leaf water and dry matter contents. The correlation scalogram (which resulted from the relationship between wavelet power and leaf water content of numerous samples) facilitated the selection of features that were most sensitive to the changes in leaf water content.

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