SPECTROSCOPIC DETERMINATION OF LEAF WATER CONTENT USING CONTINUOUS WAVELET ANALYSIS

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1. INTRODUCTION

The remote detection of plant water status plays an important role in the assessment of moisture stress, the assessment of wildfire risk and the monitoring of physiological status of plants [1]. In the past decade the estimation of leaf water content from remotely sensed reflectance has focused on the equivalent water thickness (EWT) defined as the leaf water mass per unit leaf area. In contrast, few studies have investigated the estimation of leaf water content as a percentage of dry mass (LWC_D) which is an input variable in forest fire risk models [2], [3]. Previous studies have examined a limited number of plant species or a narrow range of water content values and thus the derived predictive models have limited general applicability for more complex datasets. In this study we report an effective approach, using continuous wavelet analysis, to determine LWC_D from reflectance spectra for a wide range of tropical forest species. The method relies on wavelet features (wavelet coefficients) that are strongly sensitive to the change in LWC_D and insensitive to the variation in leaf structural properties across species.

2. STUDY SITE AND DATASETS

Leaf samples were collected in March 2007 at two sites in Panama. The first site is located at Parque Natural Metropolitano (PNM) in a tropical dry forest and the second at Fort Sherman (FS) in a tropical wet forest [4]. Annual rainfall is approximately 1740 mm at PNM and 3300 mm at FS. Twenty-three species of lianas and eight species of trees were sampled at PNM; eight species of lianas and eight species of trees were sampled at FS. Spectral reflectance from 400-2500 nm was measured for each of the 265 leaf samples. In addition, leaf fresh weight and dry weight were determined and leaf water content (LWC_D) was measured as the ratio of leaf water mass to dry mass.

3. METHODS

3.1 CONTINUOUS WAVELET ANALYSIS

Continuous wavelet analysis (CWA) has recently emerged as a promising tool in reflectance spectroscopy to estimate chlorophyll content from the spectra of leaves [5] or bitumen content from the spectra of oil sands [6]. With a continuous wavelet transform, the leaf reflectance spectra are decomposed into a number of scale components and each component is directly comparable to the reflectance spectra. The multiscale property of CWA has the potential to characterize the variations in overall reflectance amplitude and localized spectral shapes arising from the change in leaf water content [5].

3.2 SELECTION OF WAVELET FEATURES AND PREDICTIVE MODELS

A continuous wavelet transform was applied to all reflectance spectra to calculate the wavelet power as a function of wavelength for ten dyadic scales (scale1=2^1, scale2=2^2, …, scale10=s^{10}). The Mexican Hat wavelet [7] was chosen as the mother wavelet. The wavelet data resulting from each reflectance spectra were stored as wavelet scalograms with dimensions of power, wavelength, and scale. Pearson's correlation was then established between each element of the wavelet power scalograms and the LWC_D of leaf samples. The outcome was a correlation scalogram which compiles the correlation coefficient (R^2) of LWC_D with wavelet power as a function of wavelength and decomposition scale. Features characterized by the highest 1% R^2 values were retained and these defined eight spectral feature regions of high correlation with leaf water content. Within each feature region, the feature with highest R^2 was retrieved and a list of eight wavelet features characterized by wavelength and scale was compiled for the estimation of LWC_D.

A series of linear regression models were examined to predict LWC_D. For this purpose 60% of the dataset was used for calibration of the models. For each model, the remaining 40% of the data was used to estimate the LWC_D and report the accuracy of the model in terms of R^2 and root mean squared error (RMSE). First we examined regression models using the eight individual wavelet features followed by a combination of wavelet features. These models were then compared to that obtained using the moisture stress index (MSI), the normalized difference water index (NDWI) and the water index (WI) computed from the reflectance data.

4. RESULTS

The eight wavelet features utilized for the estimation of LWC_D are located in the shortwave infrared region (1300-2500 nm) [Fig. 1]. Two features at high scales (scale 6 and 7) are found on the slope of two strong water absorptions and capture the variation in reflectance amplitude with varying LWC_D. Most of the remaining features capture changes in spectral shape arising from the varying strength of absorptions by dry matter (e.g., lignin, cellulose and protein), especially the significant changes from 1650-1850 nm and 2000-2230 nm regions [Fig. 1]. The eight wavelet features achieved good estimations of LWC_D when examined individually with the lowest RMSE of 28.34% and highest R^2 for a feature at 2165 nm [Table 1]. On the other hand the spectral indices

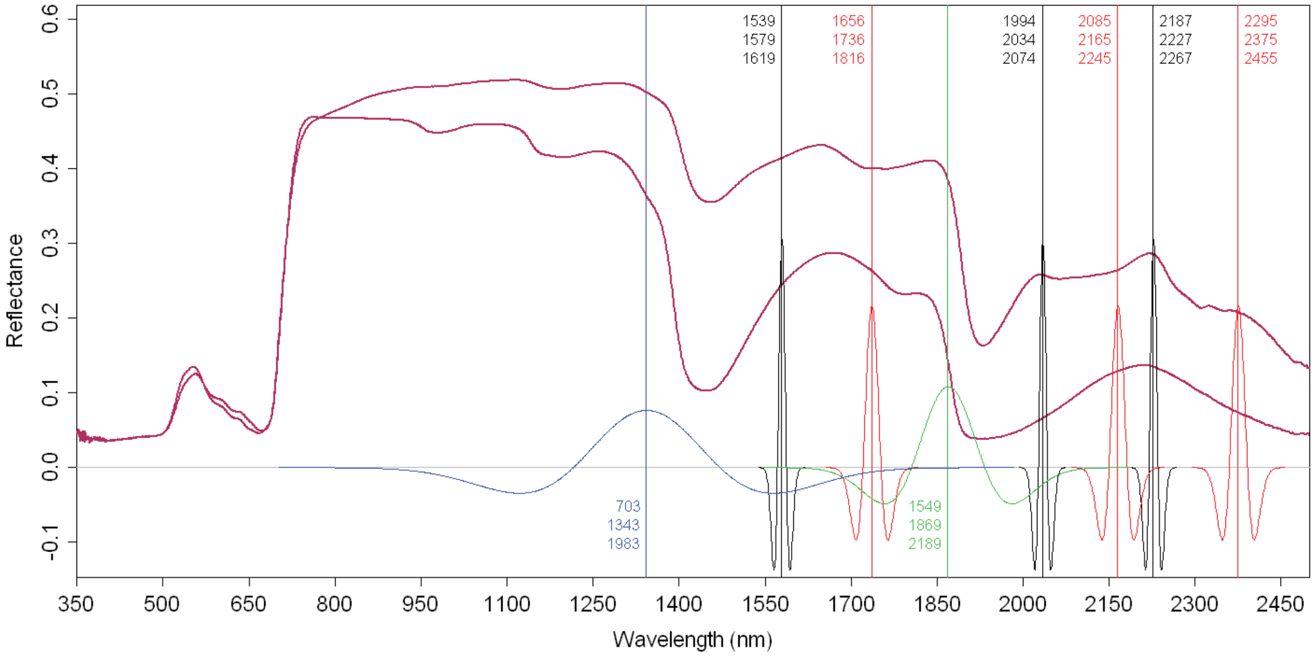

Fig. 1. Position of wavelet features color coded by scale. Also shown for each feature is the associated Mexican Hat wavelet. The two reflectance spectra illustrate differences in LWC_D and represent leaves with highest (top, 32.31%) and lowest (bottom, 418.18%) LWC_D. The three numbers beside every vertical line identify the wavelength of start, center and end points of the wavelet. Black, red, green and blue are for scale 3, 4, 6 and 7, respectively.

for water detection were weakly correlated to LWC_D ($R^2<0.01$). The combination of the eight wavelet features improved the estimation slightly and gave an RMSE of 26.04%.

5. CONCLUSION

The use of continuous wavelet analysis proved to be an effective approach to estimate leaf water content as a percentage of dry mass for a range of tropical forest species on trees and lianas. Commonly cited spectral indices could not capture the spectral responses due to changes in LWC_D and thus could not predict LWC_D. The wavelength position of the wavelet features indicates that absorptions due to leaf dry matter play a critical role in the estimation of LWC_D.

Table 1. The accuracy of regression models for the estimation of LWC_D

	Wavelet features*								
	(2165, 4)	(1343, 7)	(1869, 6)	(1736, 4)	(2375, 4)	(2034, 3)	(1579, 3)	(2227, 3)	C**
R^2	0.66	0.60	0.55	0.48	0.44	0.45	0.46	0.44	0.71
RMSE (%)	28.34	30.69	32.62	35.22	36.51	36.06	35.91	36.45	26.04

* Individual wavelet features are characterized by wavelength (nm) and scale. For example, (2165, 4) denotes a feature of 2165 nm at scale 4. ** C is a stepwise selection from the combination of the eight features.

6. REFERENCES

[1] B. Datt, “Remote sensing of water content in *Eucalyptus* leaves,” *Aust. J. Bot.,* vol. 47, 909-923, 1999.

[2] F. M. Danson and P. Bowyer, “Estimating live fuel moisture content from remotely sensed reflectance,” *Remote Sens. Environ.,* vol. 92, pp. 309-321, 2004.

[3] D. Riaño, P. Vaughan, E. Chuvieco, P. J. Zarco-Tejada, and S. L. Ustin, “Estimation of fuel moisture content by inversion of radiative transfer models to simulate equivalent water thickness and dry matter content: Analysis at leaf and canopy level,” *IEEE Trans. Geosci. Remote Sens.,* vol. 43, no. 4, pp. 819-826, Apr. 2005.

[4] G. A. Sánchez-Azofeifa, K. Castro, S. J. Wright, J. Gamon, M. Kalacska, B. Rivard, S. A. Schnitzer, and J. L. Feng, “Differences in leaf traits, leaf internal structure, and spectral reflectance between two communities of lianas and trees: Implications for remote sensing in tropical environments,” *Remote Sens. Environ.,* vol. 113, pp. 2076-2088, 2009.

[5] G. A. Blackburn and J. G. Ferwerda, “Retrieval of chlorophyll concentration from leaf reflectance spectra using wavelet analysis,” *Remote Sens. Environ.,* vol. 112, pp. 1614-1632, 2008.

[6] D. Lyder, J. Feng, B. Rivard, A. A. Gallie, and E. Cloutis, “Remote bitumen content estimation of Athabasca oil sand from hyperspectral infrared reflectance spectra using Gaussian singlets and derivative of Gaussian wavelets,” *Fuel*, vol. 89, pp. 760-767, 2010.

[7] C. Torrence and G. P. Compo, “A practical guide to wavelet analysis,” *Bull. Amer. Meteorol. Soc.,* vol. 79, no. 1, pp. 61-78, 1998.