Retrieval of leaf water content spanning the Visible to Thermal infrared spectra

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Abstract

The objective of this study was to investigate the entire spectra (from visible to the thermal infrared; 0.390 µm -14.0 µm) to retrieve leaf water content in a consistent manner. Narrow-band spectral indices (calculated from all possible two band combinations) and a partial least square regression (PLSR) were used to assess the strength of each spectral region. The coefficient of determination (R^2) and root mean square error (RMSE) were used to report the prediction accuracy of spectral indices and PLSR models. In the visible-near infrared and shortwave infrared (VNIR-SWIR), the most accurate spectral index yielded R^2 of 0.89 and RMSE of 7.60%, whereas in the mid infrared (MIR) the highest R^2 was 0.93 and RMSE of 5.97%. Leaf water content was poorly predicted using two-band indices developed from the thermal infrared (R^2=0.33). The most accurate PLSR model resulted from MIR reflectance spectra (R^2=0.96, RMSE=4.74% and $RMSE_{CV}$=6.17%) followed by VNIR-SWIR reflectance spectra (R^2=0.91, RMSE=6.90% and $RMSE_{CV}$=7.32%). Using thermal infrared (TIR) spectra, the PLSR model yielded a moderate retrieval accuracy (R^2=0.67, RMSE=13.27% and $RMSE_{CV}$=16.39%). This study demonstrated that the MIR and SWIR domains were the most sensitive spectral region for the retrieval of leaf water content.

Keywords; Water stress, remote sensing, VNIR-SWIR, MIR, TIR, statistical models

1. Introduction

An accurate estimation of leaf water content permits for example monitoring plant physiological status (Datt 1999), predicting drought risk (Bauer et al. 1986), precision agriculture (Peñuelas et al. 1993; Peñuelas et al. 1997) and assessing the risk of forest fire (Chuvieco et al. 2002). Remote sensing is a promising tool for assessing vegetation water status due to its capability of providing continuous spatial observations over large areas compared to point based measurements in the field (Hunt et al. 1987; Hunt and Rock 1989; Sepulcre-Cantó et al. 2006).

Retrieving leaf water content using remote sensing data, has been widely investigated in the visible near infrared (VNIR) and shortwave infrared (SWIR) spectra (Thomas et al. 1971; Danson et al. 1992; Aldakheel and Danson 1997; Ceccato et al. 2001; Cheng et al. 2011). Water molecules in leaves strongly absorb electromagnetic energy in the NIR (0.720 – 1.00µm) and SWIR (1.40 – 1.90 µm) (Thomas et al. 1971; Datt 1999). The estimation of leaf water content using NIR is less effective, and the spectral response is less sensitive with changing leaf water content, compared to the SWIR (Datt 1999). Other studies found that leaf water content is strongly correlated with reflectance and derivative spectra at wavebands between 1.40 – 1.90 µm while wavebands between 1.90 – 25 µm are relatively less sensitive to the variation in leaf water content (Danson et al. 1992; Ceccato et al. 2001; Ceccato et al. 2002b; Champagne et al. 2003). The wavebands between 1.40 – 1.90 µm contain water absorption features and are strongly related to leaf water content (Hunt et al. 1987; Bowman 1989).

60 Very few studies attempted to estimate leaf water content using the MIR and TIR spectra.
61 However, there are strong specific water absorption features located in the MIR (at 2.90, 4.65,
62 and 6.08 µm) which may potentially be a suitable region for quantifying leaf water status
63 (Wieliczka et al. 1989). Using visible to MIR (0.4 – 5.7 µm), Gerber et al. (2011) recently
64 modeled the Directional Hemispherical Reflectance (DHR) and transmittance spectra of fresh
65 and completely dried leaves. Using two different (independent) datasets, they noticed
66 considerable variation with changing leaf water content in the MIR domain (Gerber et al. 2011).
67 More recently, Fabre et al. (2011) studied the effect of leaf water content on spectral reflectance
68 in the MIR to TIR (3.0–15.0 µm). The variation in spectral response of the three plant species
69 used was more pronounced in the MIR compared to the TIR (Fabre et al. 2011). The variation in
70 MIR spectra with varying leaf water content was quantified and resulted in a high correlation
71 with leaf water content. This strong correlation led to the successful estimation of leaf water
72 content from MIR spectra using various spectral transformation techniques (Ullah et al. 2012c;
73 Ullah et al. 2013).

74 The above studies either used VNIR– SWIR or MIR and TIR but they did not sample the same
75 target for the entire range from visible to thermal infrared to guarantee consistency in
76 measurement. In the current study, we report on research where the same leaf samples were
77 measured simultaneously across the visible to thermal infrared. Moreover, the intermediate water
78 levels were acquired by successively dehydrating leaves. The main objective of this study was to
79 assess the strength of the entire spectra (from visible to thermal infrared) for the estimation of
80 leaf water content. The reflectance and first derivative spectra in the visible to thermal infrared
81 domain were assessed using various water stress indices (e.g. by establishing univariate
82 regression) and partial least square regression (PLSR; a type of multivariate regression analysis).

2. Material and Methods

2.1 Leaf sampling and measurements of leaf water content.

Leaves (six samples per species) were collected from various plant species (Table 1) in the vicinity of the ITC building (in Enschede, the Netherlands) during July and August 2011. Before the first spectral measurements, leaves attached to small twigs, were keep moist in cotton to avoid desiccation (Kumar et al. 2010). The leaves were then progressively dehydrated at room temperature and measurements were taken after every four hours. Before the final reading, leaves were oven dried at 60 °C for one and a half hour. The leaves mass were precisely measured using a digital weight balance with 100 µg accuracy.

The leaf water content (LWC_f) was calculated using the following formula (Ullah et al. 2013);

$$LWC_f = 100(Mw - Md)/ Mw$$

where *Mw* represents the mass of the wet leaf and *Md* is the mass 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.

We sampled 402 measurements from eleven different plant species. The number of leaves sampled per species and the dehydration phases are detailed in Table 1.

Insert Table. 1 about here

2.2 Spectral measurements

103 The spectral measurements were recorded between 0.390 and 14.0 µm. To cover the entire
104 spectral range (visible, NIR, SWIR, MIR and TIR); two different spectrometers were used for
105 the measurements. The ASD FieldSpec® spectro-radiometer (Analytical Spectral Devices:
106 Boulder, CO, USA) covered the VNIR-SWIR range (0.390–2.50 µm), whereas a Bruker
107 VERTEX 70 FTIR (Fourier transform infrared; Bruker Optics GmbH, Ettlingen, Germany)
108 spectrometer was used to acquire Directional Hemispherical Reflectance (DHR) between 2.50 –
109 14.0 um. During spectral measurements of the leaf samples, the ASD and Bruker spectro-
110 radiometers were used in random order to minimize the influence of different spectral
111 instruments.

112 An ASD spectrometer, coupled with an integrating sphere, was used to measure reflectance
113 spectra between VNIR and SWIR (0.390–2.50 µm; comprising 2110 spectral bands). The ASD
114 is a portable spectrometer and can acquired spectra with a sampling interval of 1 nm. Two
115 hundred (200) scans were averaged to a single spectrum in order to minimize the effect of noise
116 (signal variance) on the final correlation analysis (see section 2.5). A calibrated reference
117 standard (with approximately 99% reflectance) was used to convert raw radiance to reflectance.

118 A Bruker VERTEX 70 FTIR acquired DHR spectra between 2.5 and 14.0 µm of the adaxial
119 surface of the leaf. The spectrometer was purged of water vapor and carbon dioxide using
120 nitrogen gas. A Mercury Cadmium Telluride (MCT) detector (cooled with liquid N_2) was used to
121 measure leaf spectra with a spectral resolution of 4^{-cm} (Hecker et al. 2011; Ullah et al. 2012a;
122 Zaini et al. 2012). Each spectrum was calibrated using a high reflectance (approximately 0.96)
123 gold plate (infragold; Labsphere reflectance technology). Each spectrum was calculated from
124 the average of 1000 scans.

125 **2.3 Preprocessing of spectra and spectral transformation.**

126 The spectra were smoothed using a Savitsky–Golay filter (Savitzky and Golay 1964), with 15
127 sample points and second order polynomials. The smoothed spectra were then used for
128 calculating different indices and first derivatives reflectance (FDR).

129 **2.4 Narrow band indices.**

130 A narrow band simple ratio, simple difference and normalized difference indices (Hunt and Rock
131 1989; Gao 1996; Peñuelas et al. 1997) were calculated for all band combinations using the
132 reflectance spectra. These indices have been reported in the literature for the VNIR–SWIR (Datt
133 1999; Ceccato et al. 2001; Zygielbaum et al. 2009), but are hardly used in the MIR and TIR
134 (Ullah et al. 2013). Different naming conventions are used for the indices in the VNIR-SWIR
135 and MIR and TIR for their interpretation (see details in Table 2).

136 Narrow band vegetation indices have been successfully used to estimate vegetation parameters
137 (Mutanga and Skidmore 2004; Darvishzadeh et al. 2008). The notion of calculating vegetation
138 indices (i.e. simple ratio, normalized difference indices) are based upon the contrast in the
139 reflectance between two spectral bands (Rouse et al. 1974). In vegetation indices, a limited
140 number of wavebands (which contain most of the information) are used from massive
141 hyperspectral wavebands. The purpose of using vegetation indices is to minimize the variability
142 in reflectance caused by various factors such as illumination condition, instrument noise,
143 atmospheric condition and soil background (van Leeuwen and Huete 1996). To determine the
144 best narrow band index, all possible combination of two bands were calculated and a

145 combination that has the highest R^2 with leaf water content was located (Thenkabail et al. 2000;
146 Mutanga and Skidmore 2004).

147 **Insert Table. 2 about here**

148

149 2.5 **Statistical analysis**

150 **2.5.1 Simple Linear regression**

151 Simple linear regression was used to quantify the retrieval accuracy of leaf water content using
152 the calculated indices. The data were randomly divided in to calibration and validation subsets.
153 The model was trained with a calibration subset (n= 268; two third of the entire dataset) and was
154 then used to predict the leaf water content in validation subsets (n= 134; one third of the entire
155 dataset). The predicted leaf water content was plotted against the measured leaf water content,
156 and the accuracy of each index reported using R^2 and RMSE.

157 **2.5.2 Partial least square regression (PLSR)**

158 A challenge associated with hyperspectral data is a high spectral dimensionality and a high
159 degree of collinearity of the adjacent bands (Vaiphasa et al. 2005). Multivariate regression
160 models based on hyperspectral data suffers from multi-collinearity especially when the numbers
161 of predictors are equal or higher in number than sample observations and the input data lead to a
162 high R^2 (Curran 1989). PLSR is a robust technique which can handle high dimensional
163 hyperspectral datasets for predicting leaf bio-chemicals, while minimizing multi-collinearity and
164 model over-fitting (Thomas and Haaland 1990). This technique has been successfully used to
165 estimate several leaf bio-chemicals (Huang et al. 2004; Asner and Martin 2008; Ramoelo et al.

2011). The Partial least square regressions (PLSR) were used to estimate leaf water content from both the reflectance and FDR spectra in the VNIR-SWIR, MIR and TIR. The increased use of PLSR in remote sensing (Lin et al. 2007; Asner and Martin 2008; Darvishzadeh et al. 2008; Ramoelo et al. 2011) is due to the fact that PLSR can process multi-collinear predictors (hyperspectral data) by inputting all spectral bands simultaneously and select uncorrelated variables from a matrix of explanatory variables (Geladi and Kowalski 1986). The PLSR analysis was implemented using the TOMCAT toolbox in MATLAB. The independent variables were first mean centered prior to input to the PLSR. The lowest $RMSE_{CV}$ (RMSE-leave-one-out cross validation) was adopted as criterion to select the optimal number of components for model development (Darvishzadeh et al. 2008). The accuracy of the models using different spectral domains was assessed using R^2, RMSE and $RMSE_{CV}$.

3. Results

3.1 Effect of leaf water content on spectral responses

The leaf water content was variably correlated with reflectance across spectral bands (Fig.1). The correlation was low between leaf water and the blue part of the spectrum (0.390–0.430 µm) and increased in the green and red part of the visible spectrum (0.50-0.65 µm; Fig.1 a). The correlation attained a maximum between 1.4 and 2.2 µm (in the SWIR). In the MIR domain, leaf water content was strongly correlated with the Directional Hemispherical Reflectance (DHR) between 2.50 and 2.70 µm, and the correlation became weaker at 2.7 to 3.6 µm. After 3.6 µm the correlation increased to a maximum between 4.0–5.6 µm (Fig 1 b). In the thermal infrared the correlation plot (Fig.1c) exhibited a flat line.

Insert Figure. 1 about here

3.2 Leaf water content and spectral indices

Using visible near infrared and shortwave infrared (VNIR-SWIR) spectra, the narow-band indices (NDWI, SRWI and DWI) were calculated and leaf water content was estimated based on these indices. The indices with the most sensitive waveband combinations yielded a high R^2 (Fig.2) using the caliberation dataset. The models derived from the calibration data were applied to the validation datasets in order to predict leaf water content. For the VNIR-SWIR domain, the prediction of leaf water content was high (R^2=0.86 (minimum), RMSE=8.86% (maximum)) using the validation datasets. For all possible waveband combinations of the three indices, the most senstive waveband combinations (with highest R^2) were located in the SWIR region (i.e. the blue rectangle in Fig.2). For the VNIR and SWIR , the NDWI provided more accurate predictions of leaf water content compared to SRWI and DWI (Fig. 3), though it is noted that in all three models (NDWI, SRWI and DWI) the predicted values underestimate the measured leaf water content above approximately 50% leaf water content.

Insert Figure. 2 about here

Insert Figure. 3 about here

For the MIR, leaf water content was accurately estimated using narow-band indices (MNDWI, MSRWI and MDWI). Using the calibration datasets, these indices yielded a high R^2 (Fig. 4). When the calibration model was applied to the independent validation datasets, leaf water

content was accurately predicted (i.e. high R^2 and low RMSE) (Fig.5 and Table 3). The indices developed from TIR spectra were less effective in estimating leaf water content. Using TIR, the maximum R^2 achieved was 0.33 (from TNDWI) and lead to a poor estimation (i.e. high RMSE) of leaf water content (Fig.6, Table 3).

Insert Figure. 4 about here

Insert Figure. 5 about here

Insert Table. 3 about here

Insert Figure. 6 about here

3.3 Partial least square regression (PLSR) and leaf water content

Using the VNIR-SWIR reflectance spectra, the PLSR models (Fig.7) were slightly more accurate (R^2=0.91, RMSE =6.90 % and $RMSE_{CV}$ =7.32 %) than the PLSR models developed using the first derivative spectra (R^2=0.90, RMSE =7.14% and $RMSE_{CV}$ = 8.50%). The number of wavelength latent factors were equal (8 factors) for both the reflectance and first derivative spectra (Table 4).

Using reflectance and first derivative spectra in the MIR, both PLSR models yielded an accurate estimate of leaf water content (Fig.8). The models based on MIR reflectance spectra were more accurate (R^2 =0.96, RMSE= 4.74 and $RMSE_{CV}$= 6.14) compared to the model developed from first derivative spectra using MIR (R^2 =0.93, RMSE= 5.98 and $RMSE_{CV}$= 8.40). The number of factors involved in the models is detailed in Table 4. The PLSR models based on MIR was more

accurate (i.e. high R^2 and low RMSE) than the models developed using VNIR –SWIR spectra. The PLSR regression using TIR spectra, yielded the lowest R^2 (0.67) and highest RMSE (13.27 %) and $RMSE_{CV}$ (16.39) (Fig. 9).

The PLSR models in all spectral domains (i.e. VNIR-SWIR, MIR and TIR) improved the prediction of leaf water content (i.e. results in a higher R^2 and low RMSE) compared to the narow band indices. The most significant improvement was noticed for retrieving leaf water content using the TIR reflectance, where R^2 increased from 0.32 to 0.67 and RMSE decreased from 31.83% to 16.39 % (Table 3 and Table 4).

Insert Table. 4 about here

Insert Figure. 7 about here

Insert Figure. 8 about here

Insert Figure. 9 about here

4. Discussion

Remote sensing is potentially a viable tool to assess and monitor vegetation parameters from local (point sample) to global scales (Skidmore 2002). In the past, estimation of vegetation water content focused on the VNIR-SWIR (0.3-2.5µm). The advent of sensor technology in the MIR (2.5-6.0 µm) and TIR (8.0-14.0 µm) enables the assessment and monitoring of vegetation functions or physiological status (Ribeiro da Luz 2006; Ribeiro da Luz and Crowley 2007, 2010;

259 Ullah et al. 2012b). In this study, an empirical relationship between leaf spectra and leaf water
260 content demonstrated that MIR and SWIR were the most sensitive spectral regions ($R^2 \geq 0.86$)
261 for the estimation leaf water content. The TIR showed moderate affinity with leaf water content
262 (maximum $R^2 = 0.67$), however the performance of TIR were less accurate compared to MIR
263 and SWIR.

264 The correlation between reflectance spectra (across visible to thermal infrared) and the leaf water
265 content (Fig. 1) underlined that leaf water content is related to the spectral response, but the
266 strength of the relationship varies across VNIR-SWIR/ MIR and TIR. The spectral response was
267 strongly correlated with leaf water content (Fig.1) in the SWIR (1.4-2.5 µm) and MIR (2.5-2.7
268 µm and 3.7-5.6 µm). The findings of this study are in line with that of the previous studies where
269 two band indices were used for the retrieval of leaf water or biochemical parameters (Hunt and
270 Rock 1989; Gao 1996; Datt 1999; Ceccato et al. 2001; Ceccato et al. 2002a; Ceccato et al. 2002b;
271 Zhang et al. 2012). Using narrow-band indices, the most sensitive waveband combinations were
272 located at 1.60 µm, 1.397 µm (i.e. SWIR) and at 2.65 µm, 3.89 µm and 5.20 µm (i.e. MIR).
273 These selected sensitive wavebands (from narrow-band indices) correspond to the slope and
274 depth of water absorption features in the reflectance spectra (Datt 1999; Ceccato et al. 2001;
275 Cheng et al. 2010; Gerber et al. 2011; Ullah et al. 2012c). The selected wavebands in the SWIR
276 (1.397 µm and 1.60 µm) are related to the absorption features associated with moisture, cellulose
277 and starch in plant leaves (Curran 1989; Thenkabail et al. 2004). The selected wavebands at 3.89
278 μm and 5.20 μm (MIR) are associated with cellulose maxima at 4.0 and 5.2 μm (Fabre et al.
279 2011).

The PLSR model of the MIR reflectance spectra yielded the highest accuracy (R^2= 0.96, RMSE= 4.74% and $RMSE_{CV}$= 6.14%) (Fig.8) compared to the VNIR-SWIR (Fig.7) and TIR (Fig. 9). The PLSR models derived using first derivative spectra were less accurate than the model developed from reflectance spectra. The lower performance of the first derivative PLSR model may be due to consistent illumination conditions used in the experiment, as well as no influence of background soil/litter reflectance (Elvidge and Chen 1995).

The PLSR model is emerging as an alternative to univariate statistical analysis for estimating leaf water content as it selects the most important variables for a parsimonious model (Lin et al. 2007; Asner and Martin 2008; Darvishzadeh et al. 2008; Ramoelo et al. 2011) and can therefore be considered in general to be more practical for such analyses. Compared to narrow band indices, all the PLSR models in their respective spectral domains achieved relatively higher accuracy (Table 3 and Table 4). In this study, using the reflectance and first derivative spectra, the number of PLSR latent factors varied from 4 to 10 (Table 4).

The novelty of this study is the simultaneous and consistent sampling of the same target leaf while measuring the whole spectrum (from the visible to thermal infrared) for the retrieval of leaf water content. Integrating various imaging spectrometers data to cover the entire spectral range (i.e. visible to thermal) helps to identify the spectral bands for accurate retrieval of leaf water content at the field level and may provide a foundation for up-scaling to canopy level.

5. Conclusion

This study has used univariate and multivariate statistical techniques to examine the strength the VNIR-SWIR, MIR and TIR for the retrieval of leaf water content. Narrow band indices and PLSR were used in to analyze the spectral data. The strength of each model was assessed by

comparing the differences in the R^2 and RMSE and $RMSE_{cv}$. It is concluded that the PLSR models were more accurate (yielded high R^2 and low RMSE) compared to narrow band indices in all spectral domains and is a practical and robust technique compared to univariate statistical analysis for estimating leaf water content. The strength of predicting leaf water content using SWIR and MIR (yielded high R^2 and low RMSE) are higher than TIR. The SWIR and MIR proved highly sensitive spectral regions and hold promise for the estimation of leaf water content.

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List of figures

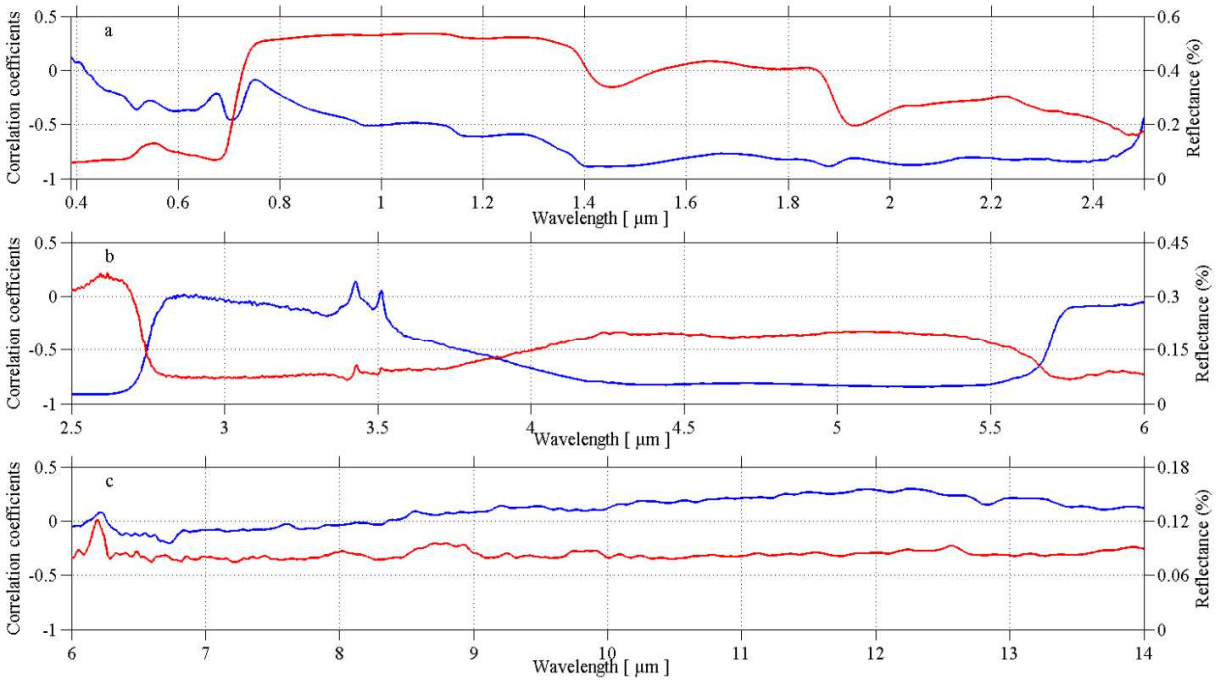
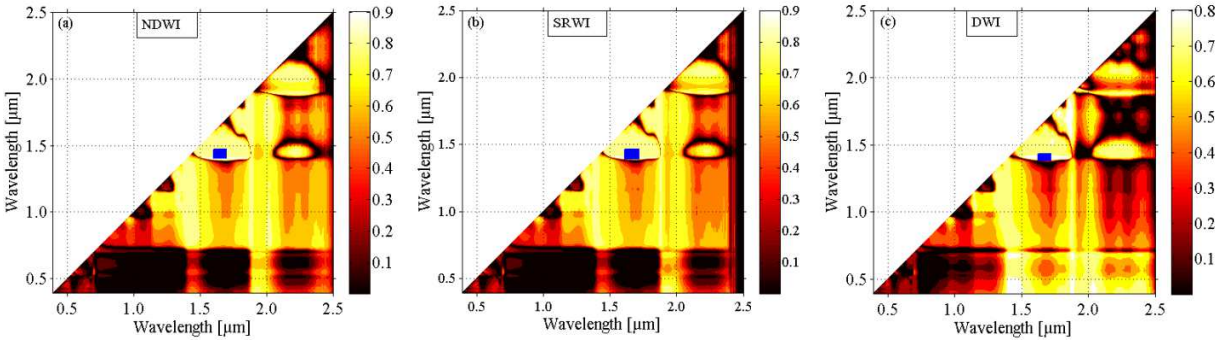


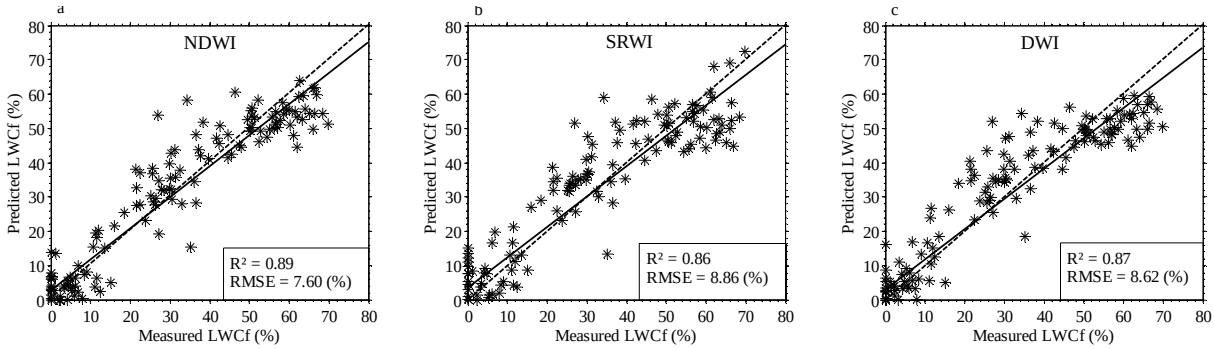
Figure 1. The relationship between spectral reflectance and the leaf water contents in the VNIR-SWIR (a), MIR (b) and TIR (c). The red line represents the average reflectance spectrum while the blue line is the correlation coefficient between leaf water content and spectral response.



456

457 Figure 2. Contour map displaying the relationship (R^2) between leaf water content and different
458 indices calculated from all possible waveband combinations from 0.390 – 2.50 μm. The blue
459 rectangles represent the most sensitive waveband regions with the highest R^2.

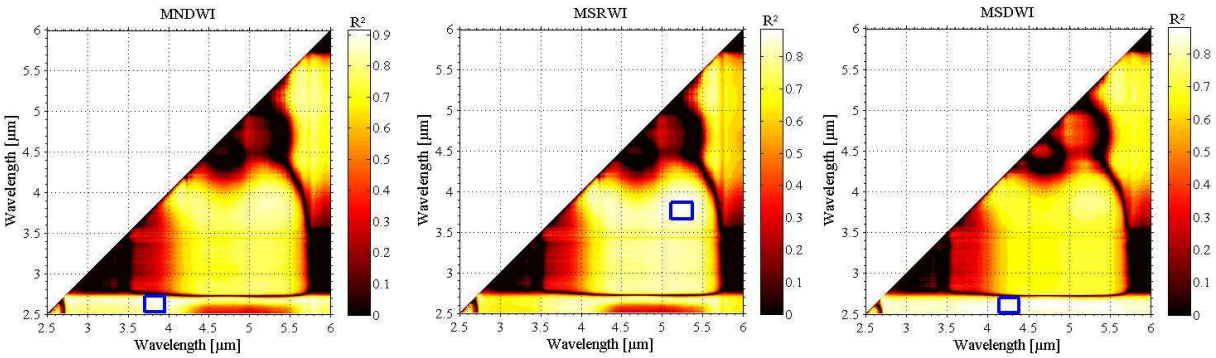
460



461

462 Figure 3. Scatterplots detailing the relationship between measured and predicted leaf water
463 content using VNIR- SWIR. The solid line shows the regression line, while the dotted line is the
464 1:1 line. The NDWI performed more accuratly compared to SRWI and DWI.

465



466

467 Figure 4. Contour map highlighting the relationship (R^2) between leaf water content and different
468 indices calculated from all possible waveband combinations from 2.50– 6.00 μm. The sensitivity
469 of different waveband combination is different. The blue rectangles represent the most sensitive
470 waveband regions with the highest R^2.

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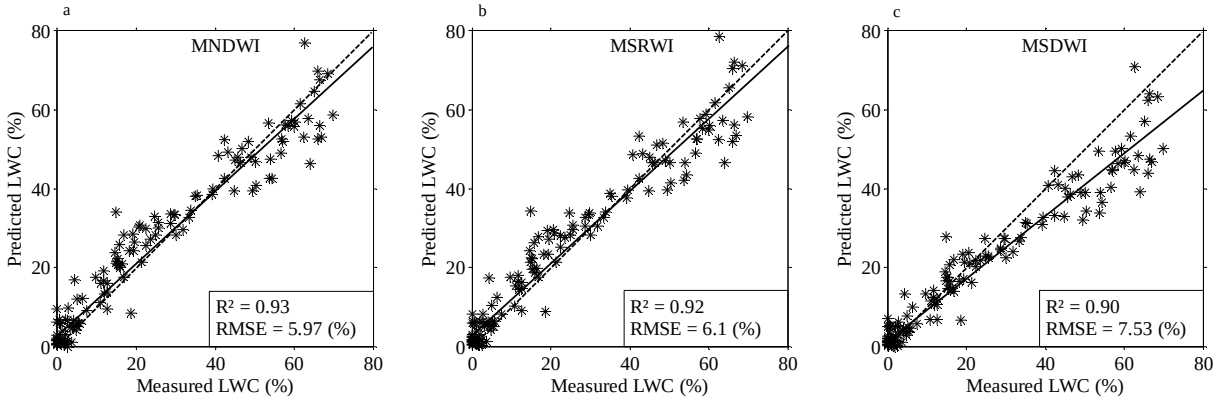


472

473 Figure 5. Scatterplot detailing the relation between measured and predicted leaf water content
474 (LWC_f (%). The predicted leaf water content is based on the calibration models developed from
475 MNDWI, MSRWI and MSDWI; the highest correlation shown produced using MNDWI.

476

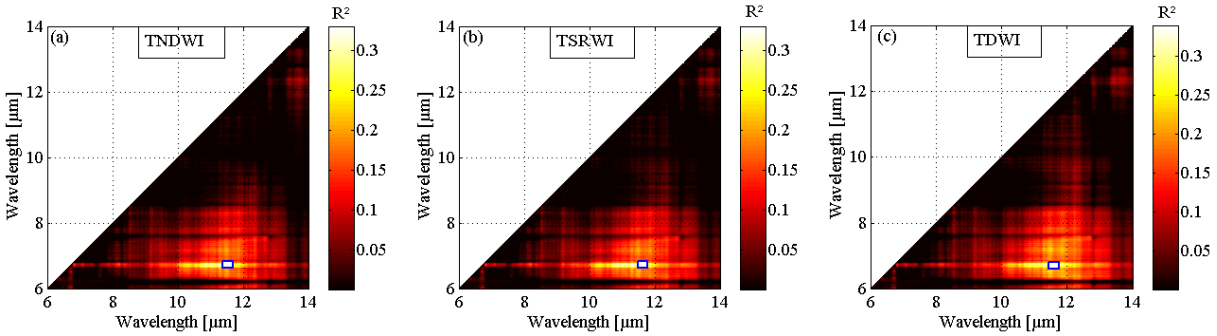
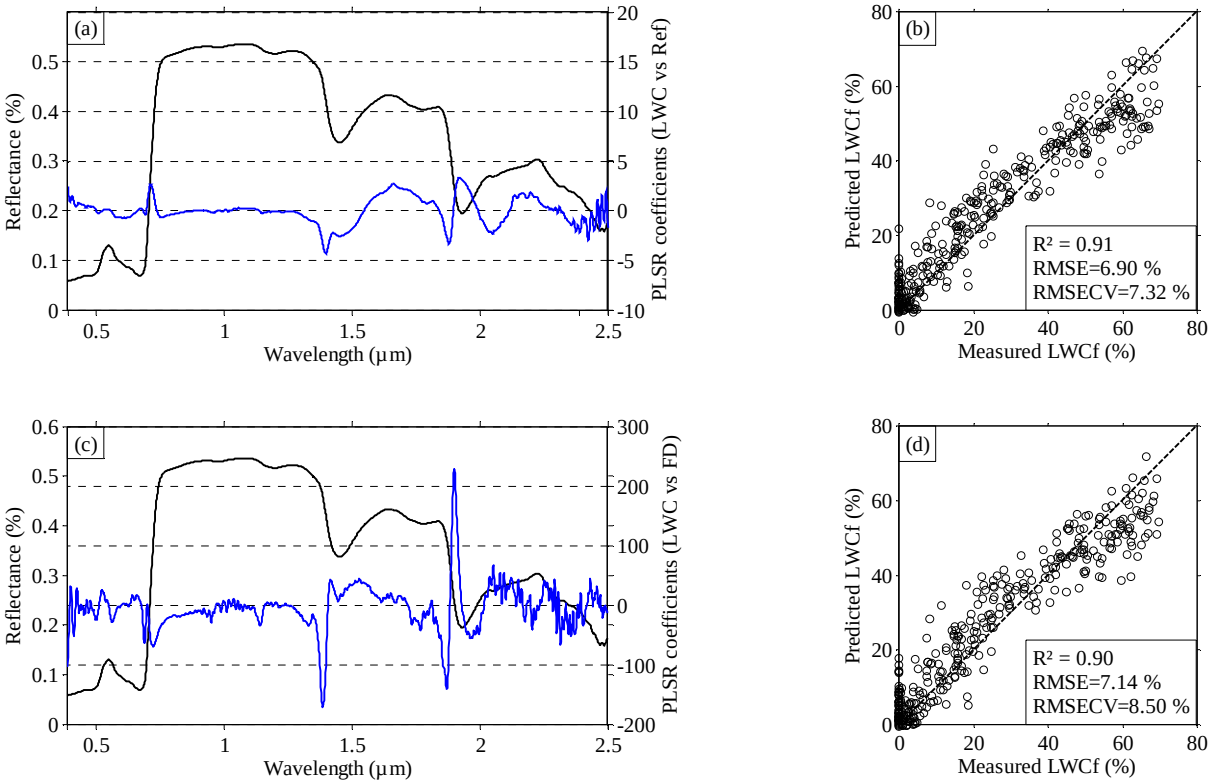


Figure 6. The relationships between leaf water content and narrow-band spectral indices in the TIR spectra. The rectangular region indicates the sensitive wavebands combination selected on the basis of the highest R^2 values.



482

483 Figure 7. The PLSR coefficients (blue line) showing the importance of each waveband in
484 developing the PLSR model for retrieving leaf water content from reflectance (a) and first
485 derivative spectra (c) in the VNIR-SWIR. The average reflectance spectra (black line) are shown
486 for reference purpose. The PLSR analysis using reflectance (b) predicted leaf water content more
487 accurately (high R^2 and low RMSE and $RMSE_{cv}$) compared to the PLSR model developed from
488 first derivative spectra (d).

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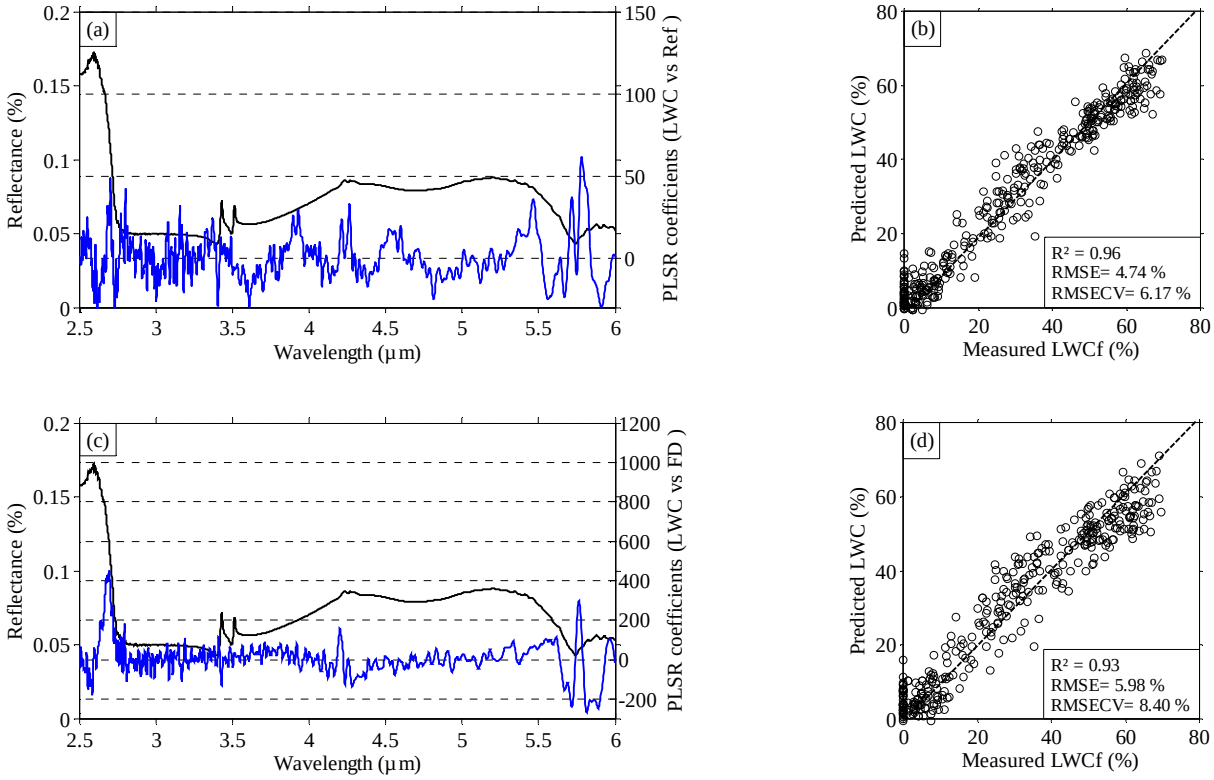
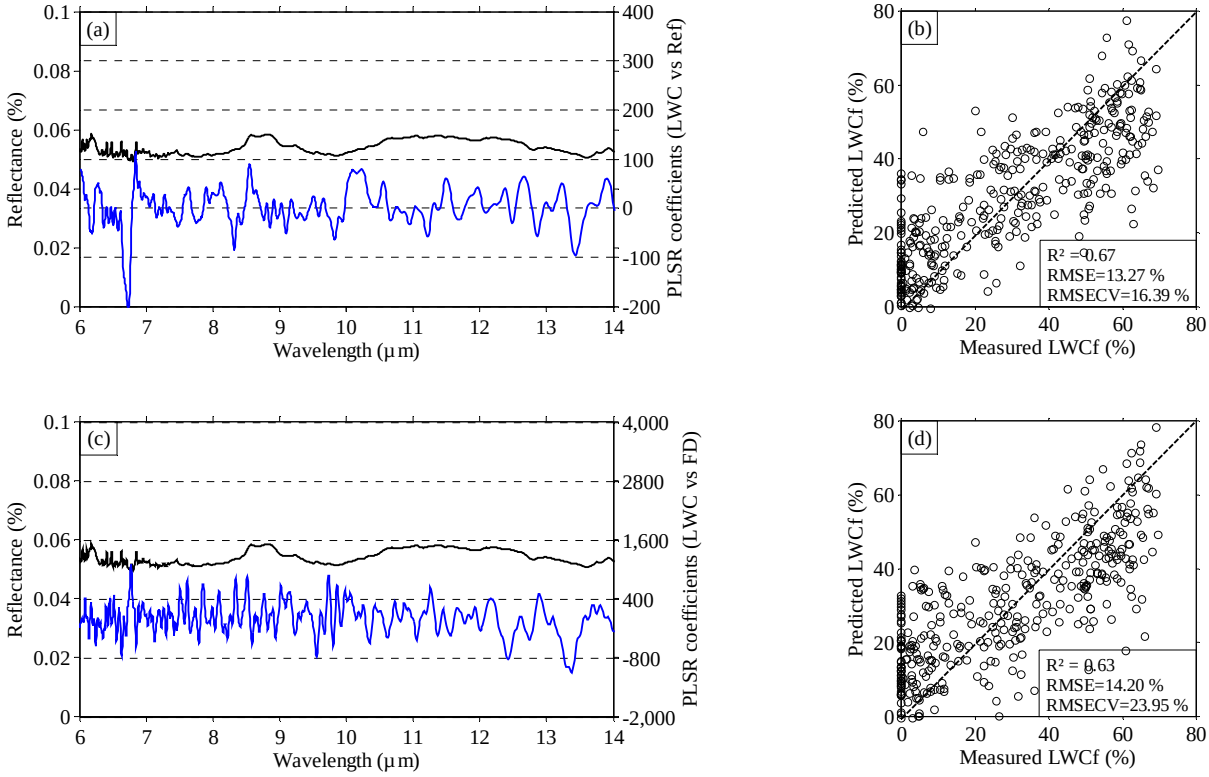


Figure 8. The PLSR coefficients (blue line) showing the importance of each waveband in developing the PLSR model for retrieving leaf water content from reflectance (a) and first derivative spectra (c) in the MIR. The average reflectance spectra (black line) are shown for reference purpose. The PLSR analysis using reflectance (b) predicted leaf water content more accurately (high R^2 and low RMSE and $RMSE_{cv}$) compared to the PLSR model developed from first derivative spectra (d).



498

499 Figure 9. The PLSR coefficients (blue line) showing the importance of each waveband in
500 developing the PLSR model for retrieving leaf water content from TIR reflectance spectra (a).
501 The average TIR reflectance spectra (black line) are shown for reference purpose. The PLSR
502 models using TIR reflectance spectra (b) and TIR first derivative spectra (d) yielded moderately
503 accurate estimate of leaf water content.

504

505 **List of Tables**

506 Table 1. Eleven plant species, their common name, Latin name, leaf sample size per species,
507 successive drying phases, and the total number of spectra measured.

Common name	Species name	Sample size	Progressive drying phases	Total spectra
Maidenhair tree	*Ginkgo biloba*	6	6	36
English ivy	*Hedera helix*	6	8	48
Norway Maple	*Acer platanoides*	6	5	30
Redosier Dogwood	*Cornus sericea*	6	6	36
Japanese Knotweed	*Fallopia japonica*	6	5	30
Oriental Planetree	*Platanus orientalis*	6	6	36
Rhododendron	*Rhododendron caucasicum*	6	8	48
Largeleaf Linden	*Tilia platyphyllos*	6	6	36
Sweetgum	*Liquidambar styraciflua*	6	7	42
European Beech	*Fagus sylvatica*	6	4	24
Horse-Chestnut	*Aesculus hippocastanum*	6	6	36
	Calibration Dataset = 268		Validation dataset =134	Total = 402

508

509

510

511 Table 2. List of spectral indices used in this study.

Name	Acronym			Equation
	VNIR-SWIR	MIR	TIR	
Normalized Difference Water Index	NDWI	MNDWI	TNDWI	$(R_{\lambda 1-} R_{\lambda 2})/ (R_{\lambda 1+} R_{\lambda 2})$
Simple Ratio Water Index	SRWI	MSRWI	TSRWI	$R_{\lambda 1}/ R_{\lambda 2}$
Difference Water Index	DWI	MDWI	TDWI	$R_{\lambda 1-} R_{\lambda 2}$
where $R_{\lambda 1}$ and $R_{\lambda 2}$ is the reflectance at two different wavebands				

512

513

514 Table 3. The most sensitive wavebands for the different indices, selected on the basis of the
515 highest R^2 values, and regression equations as calculated using the calibration datasets. The
516 validation RMSE and R^2 are displayed in the last two columns.

Index	Most sensitive bands		Calibration		Validation	
	λ_1(µm)	λ_2(µm)	R^2	Regression Eq	R^2	RMSE (%)
NDWI	1.400	1.578	0.91	y =-0.002x + 0.0368	0.89	7.60
SRWI	1.397	1.614	0.88	y = -0.0038x + 1.0694	0.86	8.86
DWI	1.396	1.615	0.87	y = -0.0014x + 0.0339	0.87	8.62
MNDWI	2.651	3.891	0.92	y = -0.0088x + 0.5562	0.93	5.97
MSRWI	3.814	5.219	0.92	y = 0.0092x + 0.5396	0.92	6.10
MDWI	2.591	4.220	0.91	y = -0.0024x + 0.1519	0.90	7.53
TNDWI	6.730	11.310	0.34	y = -0.0032x + 0.9632	0.33	31.22
TSRWI	6.730	11.310	0.33	y = -0.0019x - 0.0196	0.32	31.83
TDWI	6.730	11.460	0.34	y = -0.0002x - 0.0016	0.32	31.69

517

518

519 Table 4. The results of PLSR analysis for estimating leaf water content using the reflectance and
520 first derivative spectra in the VNIR-SWIR, MIR and TIR.

	Spectral region	No. of factors	R^2	RMSE (%)	$RMSE_{CV}$ (%)
Reflectance spectra	VNIR-SWIR	8	0.91	6.90	7.32
	MIR	10	0.96	4.74	6.14
	TIR	9	0.67	13.27	16.39
First Derivative Spectra	VNIR-SWIR	8	0.90	7.14	8.50
	MIR	4	0.93	5.98	8.40
	TIR	4	0.63	14.21	23.95

521