Annals of Agricultural & Crop Sciences

Open Access

Austin Publishing Group

Research Article

Estimation of Leaf Water Content of Different Leaves from Different Species Using Hyperspectral Reflectance Data

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Received: December 27, 2021; **Accepted:** February 08, 2022; **Published:** February 15, 2022

Abstract

Water content of individual leaves or vegetation canopies is a significant variable in plant physiological processes. The water content of the vegetation leaves plays a very significant role. The ability of hyperspectral advanced technology to accurately evaluate leaf and canopy water content has improved large-scale measures. Due to the presence of water absorption band in near and SWIR wavelength range, electromagnetic spectrum will allow us to correctly measure the leaf water content. Three different parameters were used to describe the water status: Equivalent Water Thickness (EWT), Gravimetric Water Content (GWC), and Plant Water Concentration (PWC), with leaf multi angular reflectance spectrum, to find sensitive spectral indices, to correctly assess water content of leaves in a wide range of plant species. Using spectral indices derived from multi angular reflectance spectra, we looked into the possibility for predicting leaf water content of six species in the study area. To analyze the status of leaf water, three different forms of hyperspectral indices were evaluated, including the Simple Ratio (SR), Normalized ratio wavelength (ND) and Double Difference ratio (DDn). To look over the possibility of predicting the leaf water status of the species in the study field, we proposed four new indices. The results showed that EWT is comparatively more sensitive to trace leaf water status than GWC and PWC. The best-established EWT indices were $(R_{905}\text{-}R1_{795})/(R_{1905}\text{-}R_{1935})$, R_{1350}/R_{1390}, $(R_{840}\text{-}R_{1565})/(R_{840}+R_{1565})$ and $(R_{925}\text{-}R_{1625})/(R_{925}+R_{1625})$ and the performance of the proposed hyper-spectral indices surpassed the performance of other indices in this study. The mentioned indices were then further analyzed on LOPEX and ANGERS databases for validation of our suggested indices and we come up with better results. This study indicates that spectral indices can be used and could be more reliable to predict leaf water content, but future studies will need to include more plant species and field data. The newly developed indices can be used to estimate EWT using simple laboratory measurements, making them helpful for agricultural environmental sciences and ecology related studies.

Keywords: EWT; PWC; GWC; LAI; Remote sensing; Hyperspectral indices

Introduction

The water content of the leaves and canopy is essential in many environmental processes because it plays a mjor part in activities such as plant food preparation, evapotranspiration, and total primary productivity [1,2]. Photosynthesis is influenced by the quantity of water in a plant's leaf; this information may be used to predict water stress during different growth stages. An important sign of early stress in a plant is a rapid decrease in or absence of sufficient water content [3]. As a consequence, knowing how much water is in the leaves may help you to figure out how healthy a plant is [4], drought assessment[5], wildfire hazard prediction [6], and a slew of additional environmental, agricultural, and forestry uses [7], [8]. Physiological development in plants is closely related to water availability, which also needs to be improved [9]. Traditional methods in order to collect high-quality data on leaf water content, on the other hand, have significant drawbacks: They are inefficient and objectionable, and the findings produced for a small research area usually do not properly reflect the spatial variation in leaf water content across different zones.

It has been discovered that optical approaches for determining plant water status are effective [10-16]. A spectral reflectance factor based on theoretical radiative transfer models could be used to extract and identify leaf water [17], [18] and empirical models [15], [19-23]. At the leaf level, experts identified a link between reflected spectral signature and leaf water content, which they subsequently extended to the canopy level. [15,21,22]. However, in recent decades, remote sensing has been emerged as a critical instrument and method for monitoring water condition at different scales [24,25]. So two widespread methods of remote sensing were developed, including model inversion [26] and spectral indices [27]. Based on reflectance data, these two methods were used to investigate leaf water status. The second method, which is spectral indices, is considerably better compared to the model inversion. Despite the fact that it is based on a mix of narrow and wide spectral bands, it is simpler to connect with leaf water status. By establishing the generic spectral index, we may

Citation: Yasir QM and Zhang W. Estimation of Leaf Water Content of Different Leaves from Different Species Using Hyperspectral Reflectance Data. Ann Agric Crop Sci. 2022; 7(2): 1111.

use remote sensing to evaluate vegetation quality and attract more people [25,27].

Since the reflectance factor in one, two, or more wavelength is used to calculate them, spectral indices have been used to analyze the amount of water in leaves and how it is distributed [25,28-31] Spectral indices can offer information on the change of leaf water content with varied degrees of precision at various scales using ground, aerial, and space borne sensors [30,32-34]. Because of continuous advancements in remote sensing technologies, the assessment of leaf water content and other biochemical characteristics is becoming more common. While using the hyperspectral reflectance factor, several spectral indices may be used to enhance estimate of leaf water content from various plant species [25,34-37]. They use the standard water-centered absorption bands at approximately 970, 1200, 1450, 1950, and 2500 (nm).

On the other hand, the increasing application of high spectral and spatial resolution data of leaves or plant multiple layers creates certain issues. There have been several hyperspectral indices suggested, however they have only been used to assess leaf water content in certain plant species or under specific measurement protocols [38,39]. The response of dying leaves responds differently from healthy leaves in several stages of water stresses, and as a result, leaf reflectance tends to increase throughout the dehydration process all across spectrum, 400-2500 (nm) [40-46]. Previous research has demonstrated that the leaf experiments may also provide a dataset with a wide variety of leaf water status and many other biological variables.

Because of the random orientation of individual leaves and variations in light directions, multi angular reflectance has been employed to calculate biochemical properties of leaves [47]. The distribution and amount of directional reflectance factor are regulated by the specular reflectance of a leaf's surface, which is independent of the leaf's biochemical characteristics, according to the majority of research [48-51], On the other hand, the majority of leaf reflectance measurements were made in a single direction, such as from the nadir, with a leaf clip, or with an integrating sphere [15,28,38,39]. In these studies, the impact of multi angular reflectance on the estimation of leaf water content is completely disregarded. Due to the anisotropic reflectance of plant cover, researchers observed that view angles affects the values of spectral indices [52,53].

Previous studies have reported that reflectance near 700 (nm) and its ratio to NIR reflectance spectra can track plant water stress [54,55]. Nonetheless, pigments and other variables that directly affect plant water features have a substantial impact on wavebands near 700 (nm), since they do not provide the predicted outcome. These problems are the most significant impediment to the empirical method's broader application. It is critical to investigate the use of hyperspectral reflection at various viewing angles to improve the use of high spectral and spatial resolution data in the evaluation of leaf water content for ecological, agricultural and forestry applications.

Multi angular spectral reflectance characteristics of different leaves from six plant species were determined in the lab. The main aim of the analysis was to: (1) demonstrate the relationship between the published indices and the species taken for this study and the actual response (2) to evaluate s indices based on different reflected spectra of leaf water status in the dataset. This analysis was conducted using a leaf experiment in which six different species were collected.

Materials and Methods

Experiment involving leaf sampling and dehydration experiment

Leaves of six different plant species, including Prunus *padus L., Swida alba Opiz, Epipremnum aureum, Acer saccharum Marsh, Schefflera microphylla Merr, and Pachira aquatic.* For calibration, samples were taken from Northeast Normal University's plant garden in Changchun, Jilin Province, China. As in prior experiments, we only picked healthy leaves with a uniform Colour and no visible evidence of damage [56,57]. Young, aged, and full mature leaves were chosen at random from top to the bottom of plant canopies. Senescing and ageing leaves represent those seen in plants under threat from polluted air, high temperatures, drought, and disease [58,59].

During the 2020 growing season, which runs from April to October, the reflectance parameters of leaves were tested in the laboratory. The leaves were gathered, enveloped in plastic bag with moist paper, and taken to the lab for examination. Then, on adaxial leaf surface, the angular spectral reflection was measured using the Northeast Normal University Laboratory Gonio Spectrometer System (NENULGS) [60]. NENULGS, which is equipped with an artificial light source, an ASD spectroradiometer (Analytical Spectral Devices Field Spec 4, Boulder, CO, USA), and goniometer, was previously described in detail in a prior article [60]. NENULGS has been used in various studies to accurately examine different properties of leaves [61-63]. Fresh weight was measured after taking the reflectance measurement and then air-dried to a stable weight for some time after that sample. Finally, the samples were placed under 80 °C for 36 hours in the oven to dry and dry weight was then weighed [64]. On its hemisphere, it has used the spectrum of reflection which ranges from 350 to 2500 (nm) in a variety of inclinations. In this experiment, we employed wavelengths stretch from 400 to 2500 (nm) [58,64].

Due to the structural constraints of NENULGS, the smallest portion angle that could be measured was 8, measurements in the backward scattering direction could not be performed when both viewing and incident angle are same.

While the measurements were collected, leaf sample was put on object stage, which were completely covered with dark black strips of tape. Black background has no influence on leaf reflection since it a wavelength independent reflectance factor of less than 0.05. The reflected radiance (*dLSample-lab*) from the leaf sample surface is normalized by the reflected radiance (*dLReference-lab*) from the reference surface (*Spectralon*) in the same viewing geometry to give the Bidirectional Reflectance Factor (BRF) [65] (Figure 1 and Table 1,2).

$$BRF(\lambda,\theta_s,\theta_v,\varphi_s,\varphi_v)=\frac{dL_{sample-lab}(\lambda,\theta_s,\theta_v;\varphi_s,\varphi_v)}{dL_{\mathrm{Re}\,ference-lab}(\lambda,\theta_s,\theta_v;\varphi_s,\varphi_v)}\rho\lambda \quad (1)$$

For definitions of EWT, GWCF, GWCD, and PWC see Table 3.

Leaf water status

Plant water status is measured using a variety of methods, including Equal Water Thickness (EWT), Plant Water Concentration (PWC), and Gravimetric Water Content (GWC). In this study, all three measures for evaluating the status of leaf water were used. The quantity of water content closely connected to the absorption of

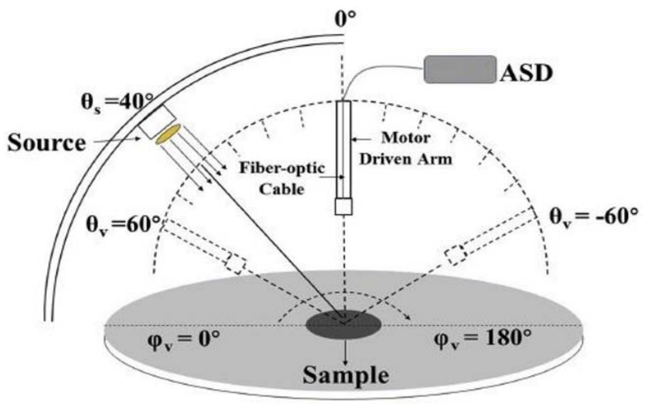

Figure 1: This figure describes the measuring system in the laboratory's principal plane. Where φ_v = 180◦ refers to the primary plane's forward scattering direction. SZA and VZA correspond to the source zenith angle (θ_s) and viewing zenith angle (θ_v) respectively.

Table 1: The Equivalent Water Thickness (EWT), Gravimetric Water Content (GWC) and PWC of the samples used in this study were determined using the geometries and statistics listed below. These samples were applied to create spectral index correlations, whereas EWT, GWC, and PWC basically used them as calibration data.

Name	Samples		EWT (g/cm²)	GWC_F (g/g)	GWC_D (g/g)	PWC (%)
Prunus padus L.	20	Min	0.0059	0.4511	0.8218	82.18
		Max	0.0097	0.5968	1.4804	148.04
		Mean	0.0078	0.5285	1.1314	113.14
Swida alba Opiz	20	Min	0.0068	0.5602	1.2738	127.38
		Max	0.0122	0.7068	2.411	241.1
		Mean	0.009	0.6459	1.8551	185.51
Epipremnum aureum	20	Min	0.0202	0.8747	6.9867	698.67
		Max	0.0293	0.9462	17.6017	1760.17
		Mean	0.0253	0.9117	10.8147	1081.47
Acer saccharum Marsh	20	Min	0.0063	0.5869	1.4209	142.09
		Max	0.0116	0.7713	3.3732	337.32
		Mean	0.0094	0.6928	2.3796	237.96
Schefflera microphylla Merr.	20	Min	0.0268	0.8225	4.6338	463.38
		Max	0.0433	0.9196	11.4516	1145.16
		Mean	0.0347	0.8681	6.885	688.509
Pachira aquatica	20	Min	0.008	0.7523	3.0385	303.858
		Max	0.0141	0.8614	6.2192	621.929
		Mean	0.0107	0.82	4.7384	473.842

energy per unit leaf area is referred to Equivalent Water Thickness (EWT) [26]. PWC refers to the dry weight ratio, while GWC will decide on the fresh and dry leaf weight.

The equations for EWT, PWC, and GWC are given below.

$$EWT(g/cm^2) = (W_F - W_D)/LA \quad (2)$$

$$PWC = ((W_F - W_D)/W_D)100 \quad (3)$$

$$GWC_F = (W_F - W_D)/W_F \quad (4)$$

and

Table 2: Summary statistics for leaf water content (n = 120).

	Standard error of mean	Standard deviation	Coefficient of variation
EWT (g/cm²)	0.001	0.01071	0.67
GWC_F	0.013	0.1397	0.19
GWC_D	0.332	3.638	0.78
PWC	33.51	363.8	0.78
Leaf area	2.348	25.72	0.51

EWT: Equivalent Water Thickness; GWCF: Gravimetric Water Content on Fresh Leaf Mass Basis; GWCD: Gravimetric Water Content on Dry Leaf Mass Basis; PWC: Plant Water Concertation.

Table 3: Intercorrelation among variables in leaf data set (n = 120).

	leaf area	EWT g/cm²	GWC_F
EWT (g/cm²)	0.346		
GWC_F	0.120	0.706	
GWC_D / PWC	0.048	0.703	0.872

Table 4: Published water indices for leaf water status evaluation.

Index	Formula	References
Simple ratio (SR)	R_{1300}/R_{1450}	[66]
Normalized differential Water Index (NDWI)	$(R_{860}-R_{1240})/(R_{860}+R_{1240})$	[67]
Normalized Differential Water Index (NDWI)	$(R_{860}-R_{1640})/(R_{860}+R_{1640})$	[68]
	$(R_{850}-R_{2218})/(R_{850}-R_{1928})$	[69]
	$(R_{850}-R_{1788})/(R_{850}-R_{1928})$	[69]
Moisture stress index (MSI)	R_{1600}/R_{820}	[13]
Simple ratio water index (SRWI)	R_{860}/R_{1240}	[70]
Normalized difference water index centered at 1640 nm($NDWI_{1640}$)	$(R_{858}-R_{1640})/(R_{858}+R_{1640})$	[68]
Normalized difference water index centered at 2130 nm($NDWI_{2130}$)	$(R_{858}-R_{2130})/(R_{858}+R_{2130})$	[68]

$$GWC_D = (W_F - W_D)/W_D \quad (5)$$

Fresh weight, dry weight and leaf area are all represented as WF, WD, and LA, respectively.

Published leaf water status indices

Different hyperspectral indices based on multiple ratios, such as a simple ratio or a normalized ratio of different wavelengths within a particular spectrum, have been developed to evaluate plant water status. Nine other already published indices were selected for this analysis to verify their efficiency as to how they react with the data obtained in the leaf dehydration experiment for this study. The indices selected are given in Table 4 for this reason.

Choosing the optimal indices

We implemented three types of measurements: SR, ND and DDn, which are currently using extensively [27]. Plant water concentration (PWC) and Gravimetric Water Content to assess the best indices for Equivalent Water Thickness (EWT) (GWC). The equations are defined as

$$SR = R_{\lambda 1}/R_{\lambda 2} \quad (6)$$

$$ND = (R_{\lambda 1} - R_{\lambda 2})/(R_{\lambda 1} + R_{\lambda 2}) \quad (7)$$

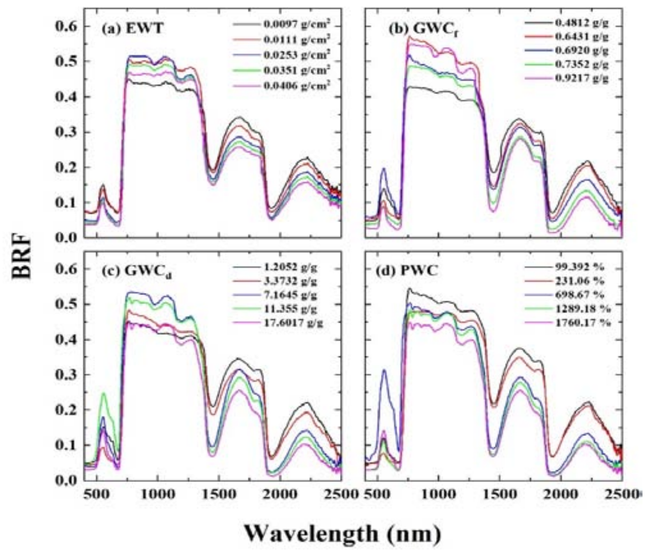

Figure 2: Bidirectional reflectance factor (BRF) of leaves with varying EWT, GWC (fresh and dry), and PWC in nadir direction. These samples are illustrative of research.

$$DDn = (R_{\lambda 1} - R_{\lambda 2}) / (R_{\lambda 1} - R_{\lambda 3}) \quad (8)$$

$R_{\lambda 1}$, $R_{\lambda 2}$ and $R_{\lambda 3}$ represent wavelengths at λ1, λ2 and λ3 respectively. While on the other hand SR, ND and DDn refer to simple ratio, normalized ratio and double difference respectively.

Statistical analysis

A dataset of 120 leaf samples from six various species was used to assess the appropriate hyperspectral indices for tracing leaf water status. Various statistical tests were run on data sets to assist in the definition of new indices and then the best selected indices were used to validate and confirm their robustness.

Further, the regression approach expands into different types, i.e., linear and nonlinear regression. The methods listed were applied to all possible wavelength combinations and wavelength interval was 5 nm using iteration method [64]. The parameters of published indices were set using lowest Root Mean Square Error (RMSE) and highest coefficient of determination (R^2). The main goal was to find indices that had the lowest RMSE while having the greatest R^2 values.

Results

Reflectance factors of leaves: Spectral characteristics and angular distribution

The spectral reflectance factors with multiple indicators at nadir View Zenith Angle (VZA) are shown in Figure 2. Spectral BRF of leaves restricted as the various water indicators extended in the nadir direction in NIR and SWIR wavelengths, due to significant absorption of leaf water at wavelengths greater than 1300 nm. These spectral features are used to estimate water content using various spectral indices. Once the distribution of multi angular reflectance factor has been taken into consideration, it may be used to comprehend the reflection characteristics of leaves from diverse species.

Performance of the published indices

Selected published indices' performance in this study was analyzed individually to assess variation in EWT, PWC, and GWC. The correlation with EWT and the chosen indices were highly significant, and they were checked individually expect two indexes $(R_{860}-R_{1240})/(R_{860}+R_{1240})$ [67] and R_{860}/R_{1240} [70]. The result came out with highest R2 and lowest RMSE. Furthermore, when all species were considered, the results were also good and having highest R2 and lowest RMSE expect two indexes $(R_{860}-R_{1240})/(R_{860}+R_{1240})$ [67] and R_{860}/R_{1240} [70]. Here it is mentioned in Table 5.

Table 5: Using measured datasets, published water indices were evaluated for EWT.

Indices	Indicators	R^2	RMSE (g/cm² or %)
R_{1300}/R_{1450}	EWT	0.845	0.004
	PWC	0.575	239.45
	GWC_F	0.472	0.102
	GWC_D	0.57	2.395
$(R_{860}-R_{1240})/(R_{860}+R_{1240})$	EWT	0.296	0.009
	PWC	0.032	359.48
	GWC_F	0.033	0.138
	GWC_D	0.032	3.595
$(R_{860}-R_{1240})/(R_{860}+R_{1240})$	EWT	0.853	0.004
	PWC	0.33	299.07
	GWC_F	0.271	0.12
	GWC_D	0.33	2.991
$(R_{850}-R_{2218})/(R_{850}-R_{1928})$	EWT	0.869	0.004
	PWC	0.401	282.85
	GWC_F	0.3	0.117
	GWC_D	0.401	2.829
$(R_{850}-R_{1788})/(R_{850}-R_{1928})$	EWT	0.916	0.003
	PWC	0.38	287.67
	GWC_F	0.34	0.114
	GWC_D	0.38	2.877
R_{1600}/R_{820}	EWT	0.847	0.004
	PWC	0.368	290.37
	GWC_F	0.288	0.118
	GWC_D	0.368	2.904
R_{860}/R_{1240}	EWT	0.295	0.009
	PWC	0.031	359.58
	GWC_F	0.034	0.138
	GWC_D	0.031	3.596
$(R_{858}-R_{1640})/(R_{858}+R_{1640})$	EWT	0.853	0.004
	PWC	0.331	298.81
	GWC_F	0.272	0.12
	GWC_D	0.331	2.988
$(R_{858}-R_{2130})/(R_{858}+R_{2130})$	EWT	0.781	0.005
	PWC	0.437	274.15
	GWC_F	0.289	0.118
	GWC_D	0.437	2.742

Table 6: Evaluation of four types of indices with reflectance for leaf EWT, PWC, GWCD and GWCF.

Indicators	Index	R^2	RMSE (g/cm² or %)
EWT	$(R_{905}-R_{1795})/(R_{1905}-R_{1935})$	0.939	0.003
	(R_{1350}/R_{1390})	0.914	0.003
	$(R_{840}-R_{1565})/(R_{840}+R_{1565})$	0.914	0.003
	$(R_{925}-R_{1625})/(R_{925}+R_{1625})$	0.895	0.004
PWC	$(R_{925}-R_{1625})/(R_{925}+R_{1625})$	0.389	285.61
	(R_{1350}/R_{1390})	0.617	226.02
	$(R_{840}-R_{1565})/(R_{840}+R_{1565})$	0.433	275.05
	$R_{925}-R_{1625})/(R_{925}+R_{1625})$	0.363	291.64
GWC_D	$(R_{905}-R_{1795})/(R_{1905}-R_{1935})$	0.389	2.856
	(R_{1350}/R_{1390})	0.617	2.26
	$(R_{840}-R_{1565})/(R_{840}+R_{1565})$	0.433	2.751
	$(R_{925}-R_{1625})/(R_{925}+R_{1625})$	0.363	2.916
GWC_F	$(R_{905}-R_{1795})/(R_{1905}-R_{1935})$	0.351	0.113
	(R_{1350}/R_{1390})	0.546	0.095
	$(R_{840}-R_{1565})/(R_{840}+R_{1565})$	0.355	0.113
	$(R_{925}-R_{1625})/(R_{925}+R_{1625})$	0.290	0.118

Newly identified leaf water status indices

Published water indices for EWT were examined using measured datasets. Finally, based on reflectance spectra, the regions with the highest R^2 and minimum RMSE value were chosen, and their results are described in Table 6. In general, particular wavelengths were strongly correlated with EWT for original reflectance and had no comparatively substantial connection with PWC, GWCD, and GWCF as shown in Table 6. Specifically the best indices were $(R_{905}-R_{1795})/(R_{1905}-R_{1935})$ having (R^2= 0.939, RMSE= 0.003), R_{1350}/R_{1390} (R^2= 0.914, RMSE= 0.003),$(R_{840}-R_{1565})/(R_{840}+R_{1565})$ (R^2= 0.914, RMSE= 0.003) and another index were$(R_{925}-R_{1625})/(R_{925}+R_{1625})$ having (R^2= 0.895, RMSE=0.004) with all measurements. These newly identified indices have a significant correlation with EWT, while PWC, GWCD, and GWCF have performed poorly. Overall, these four indices' performance with original reflectance was the best by looking to R2 and RMSE values. It is mentioned in Table 6.

In Figure 3, linear and nonlinear regression were performed to develop linear models and determine the coefficient of determination between different wave length ranges and water indices (EWT, PWC, DWCF and GWCD to compare the efficiency of the model. Nonlinear regression models performed well as compare to linear regression model almost all the studied wave length ranges.

Linear regression equation

$$y_i = \beta_0 + \beta_1 x_i \quad (8)$$

Nonlinear regression equation

$$y_i = \beta_0 + \beta_1 x_i + \beta_2 x_i^2 \quad (9)$$

Co-efficient of determination $$R^2 = 1 - \frac{\sum_{i=1}^{n}(y-y^{\wedge})^2}{\sum_{i=1}^{n}(y-y^{-})^2} \quad (10)$$

where, y_i and x_i are dependent and independent variables respectively.

Table 7: Validation datasets for calculating Equivalent Water Thickness (EWT), Gravimetric Water (GWC) and PWC in this study.

Spectrophotometer	LOPEX *Perkin Elmer Lambda 19*	ANGERS *ASD FieldSpec*
Measurement	Laboratory	Laboratory
Spectral range (nm)	400-2500	350-2500
Number of Samples	45	43
Mean (g/cm²)	0.0111	0.0116
Min (g/cm²)	0.0003	0.0044
Max (g/cm²)	0.0525	0.034
Reference	[71]	[72]

β_0 - Intercept, β_1, β_2 - slope and y ˆ represent the estimated values of dependent variables.

Validation data sets from different sources

The first set of data comes from the European Commission's Joint Research Center's Leaf Optical Properties Experiment (LOPEX), which is composed of 330 leaf samples from 45 different plant species [71]. The ANGERS dataset was prepared in 2003 in France, possesses 275 leaf samples from 43 species of plants [72] (Figue 4).

In the lab, the directional hemispherical reflectance factors of leaves from the LOPEX and ANGERS datasets were examined using a spectrophotometer with an integrating sphere. Angular effect was not included in the integrating sphere calculations (Table 7).

These LOPEX and ANGERS database were further taken into account for the validation of the indices proposed in this study to check out the reliability and generalization. For which we first calculate EWT, GWC and PWC and then find out R2 plus Root Mean Square Error (RMSE) with spectral indices proposed in this study.

In the LOPEX database it exhibits good results in terms of EWT except one index "d" as shown in Figure 5. while three indices i.e. a, b and c shows strong correlation with lowest RMSE.

While in the ANGERS database, all of the indicators were compared to the suggested one by one, and the findings, particularly in terms of EWT, were strong, with the greatest R^2 and lowest RMSE values, as shown in Figure 6.

So generally it is concluded that both the databases i.e. LOPEX and ANGERS have good results with our proposed water content indices specifically with EWT, because in other two indices which are GWC and PWC there is no role of LAI for measuring water content.

Discussion

The best indicators for defining the status of leaf water

The most frequently used measurements for leaf water indices is the Modified Difference Ratio (MDR), Normalized Difference Index (ND) and Simple Ratios (SR) which usually disrupts standard water absorbing wave lengths such as WI, NDWI and SRWI because there is variation in all these and they use different wavelengths. Our results also indicate that the status of leaf water is very sensitive to ND and SR. Among them, $(R_{905}-R_{1795})/(R_{1905}-R_{1935})$ with R^2= 0.939 and RMSE= 0.003 are the best indices, followed by R_{1350}/R_{1390} with R^2= 0.914 and RMSE= 0.003, $(R_{840}-R_{1565})/(R_{840}+R_{1565})$ with R^2= 0.914 and RMSE=

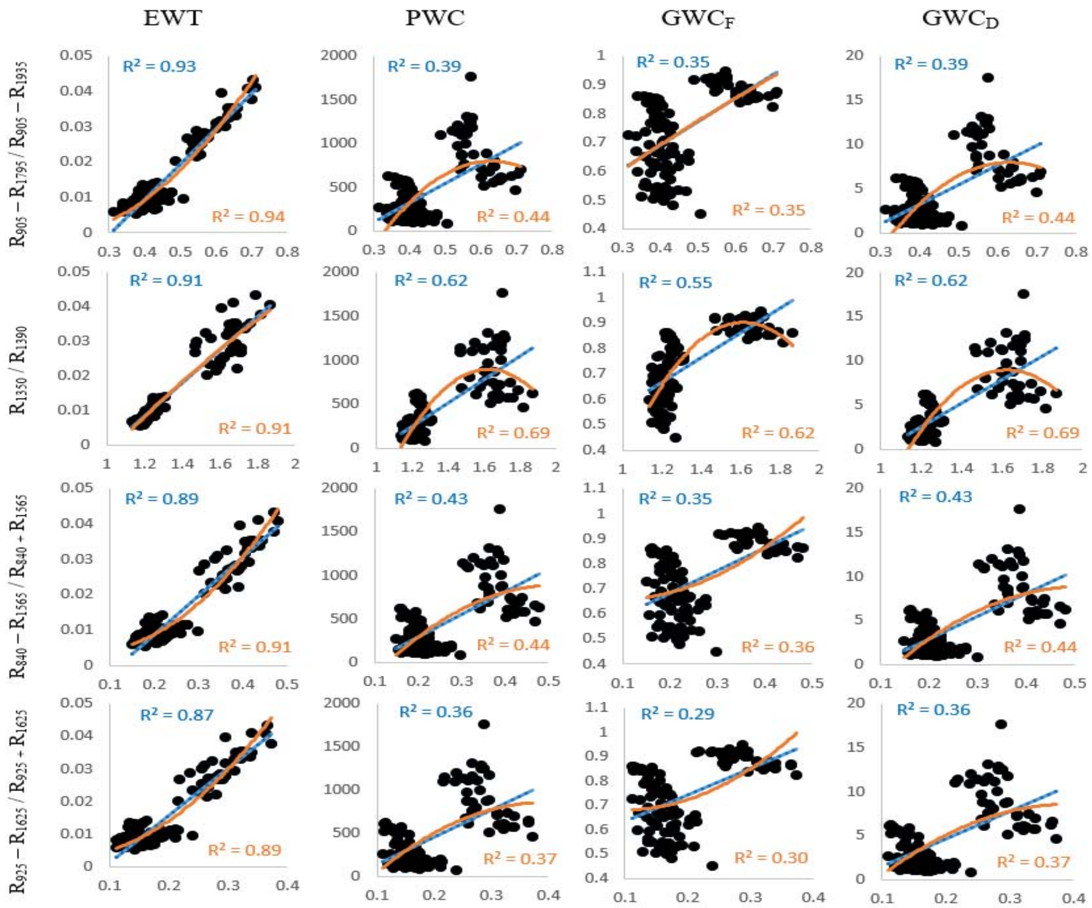

Figure 3: The coefficient of determination of chosen wave length and water indices were calculated using linear and nonlinear regression models (EWT, PWC, GWCF, and GWCD).

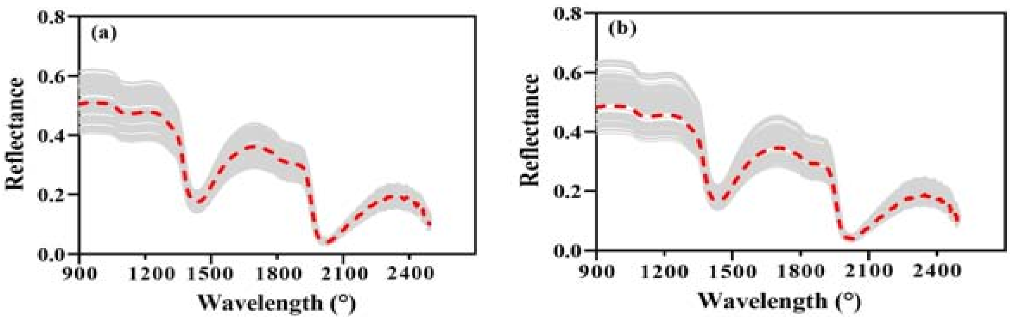

Figure 4: Spectrum of leaf reflectance from the (a) ANGERS and (b) LOPEX datasets. The dashed red line represent the median spectrum.

0.003, $(R_{925}-R_{1625})/(R_{925}+R_{1625})$ with R^2= 0.895 and RMSE= 0.004, with good results compared to the indices already published, the indices determined in the study. Therefore, the recommended indices are more reliable and consistent for calculating leaf water status during leaf dehydration. R^2 was found to be relatively stronger for EWT than others, which means that EWT is more prone to leaf water status (Figure 7). The results are shown in Table 6 and Figure 3.

The stability of the indices suggested

Figure 8 illustrates this. The newly proposed hyperspectral indices outperform other types of indices as well as the indices included in this research. A good and dependable index should theoretically be evaluated for calibration on multiple datasets of random percentages and to maintain high stability under varied wavelength resolutions. The intensity and reliability of the newly suggested indices would satisfy future applications and have the potential to be extendable to large scales. To construct these recommended indices for EWT, PWC, GWCF, and GWCD, multispectral remote sensing data is now available. Rapid advances in hyperspectral remote sensing, on the other hand, may give the answer in the near future, and it may then

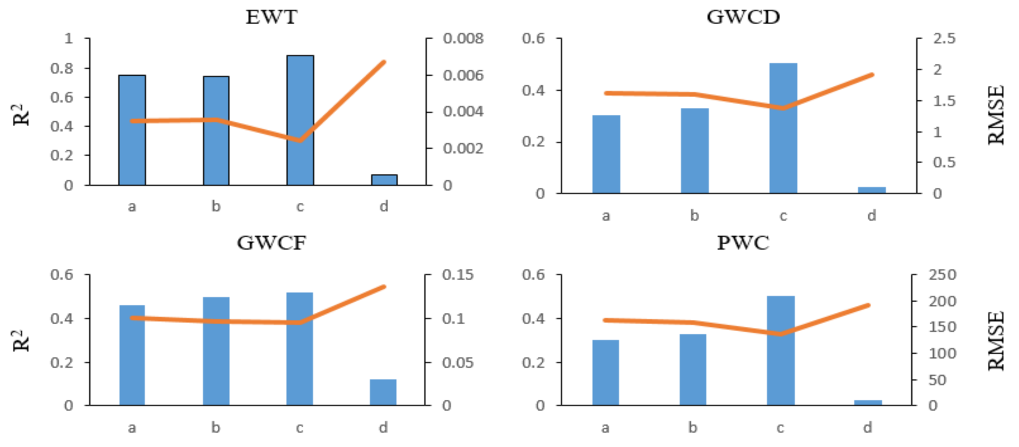

Figure 5: Where a, b, c and d refers to the proposed indices (R_{905}-R_{1795})/(R_{1905}-R_{1935}), R_{1350}/R_{1390}, (R_{840}-R_{1565})/(R_{840}+R_{1565}) and (R_{925}-R_{1625})/(R_{925}+R_{1625}) respectively.

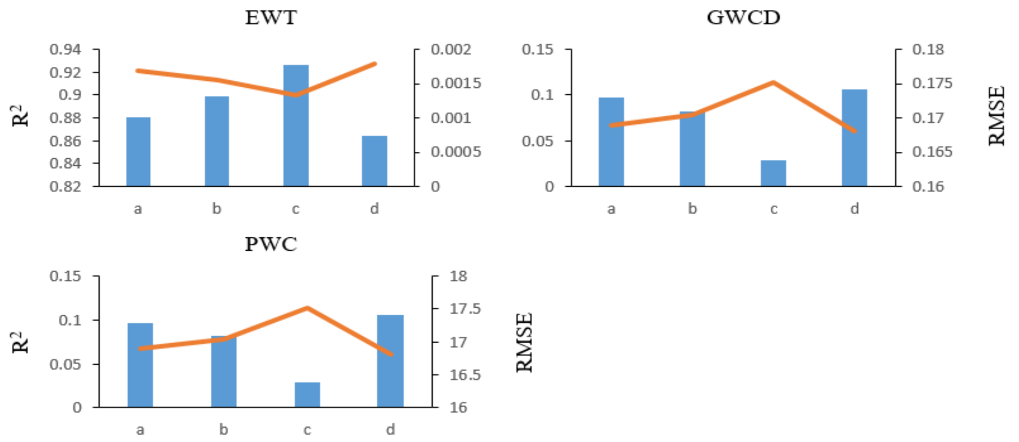

Figure 6: The suggested indices are denoted by a, b, c and d (R_{905}-R_{1795})/(R_{1905}-R_{1935}), R_{1350}/R_{1390}, (R_{840}-R_{1565})/(R_{840}+R_{1565}) and(R_{925}-R_{1625})/(R_{925}+$_{R1625)}$ respectively.

be expected to be used on a large and widespread basis.

Spectral indices' development

As interpretation given by [27,73] Testing all potential waveband combinations might aid in the development of better models. In this section, we apply the criteria of least RMSE between assessed and real content to generate optimum spectral indices i.e. the set of wavelengths that describe leaf variation, using leaf optical data simulated by sampling. Several indices were considered. The indices were chosen based on the number of wavelengths required to calculate them, allowing for the systematic calculation of all possible wavelength combinations in an acceptable period of time. Furthermore, these indices surpass others, such as basic reflectance and reflectance difference, by a substantial margin.

Leaf properties

The optical properties of dehydrated leaves changed, with relative reflectance slowly rising at various wavelengths. However, several published studies show irregularities in leaf reflectance after dryness, such as an overall increase in leaf reflectivity [74,75] a decrease [76], and no significant changes in reflectance [77,78]. Most of these studies focused on leaf and canopy structure and thickness, as well as external atmospheric changes, during various phases of plant development, canopy structures and plant leaf physiology and thickness. As a result, we employed a method that included carefully defined experimental conditions and leaf characteristics (Figure 9).

To demonstrate how the DDn type of index may be used to determine leaf biochemical properties using various combinations of center wavelength and distances. A Colour legend were used to easily distinguish which wavelength combination provide small and high RMSE value for each DDn index derived from various combination of center wavelength and distance Figure 10. Shows RMSE matrix for evaluating EWT using DDn indices.

As claimed by [79], Only EWT is associated to water absorption at the leaf or canopy level. As a result, it's more difficult to estimate EWT and other water indices from remote sensing data, especially when monitoring them at different scales. Changes in leaf internal structure and water indices cause spectral reflectance to change slightly, primarily in the infrared and near infrared.

In natural plant communities, water stress data is critical for irrigation decision-making and drought evaluation. The effectiveness of a few hyperspectral water sensitive indices for assessing EWT of diverse plant species is investigated in this research work.

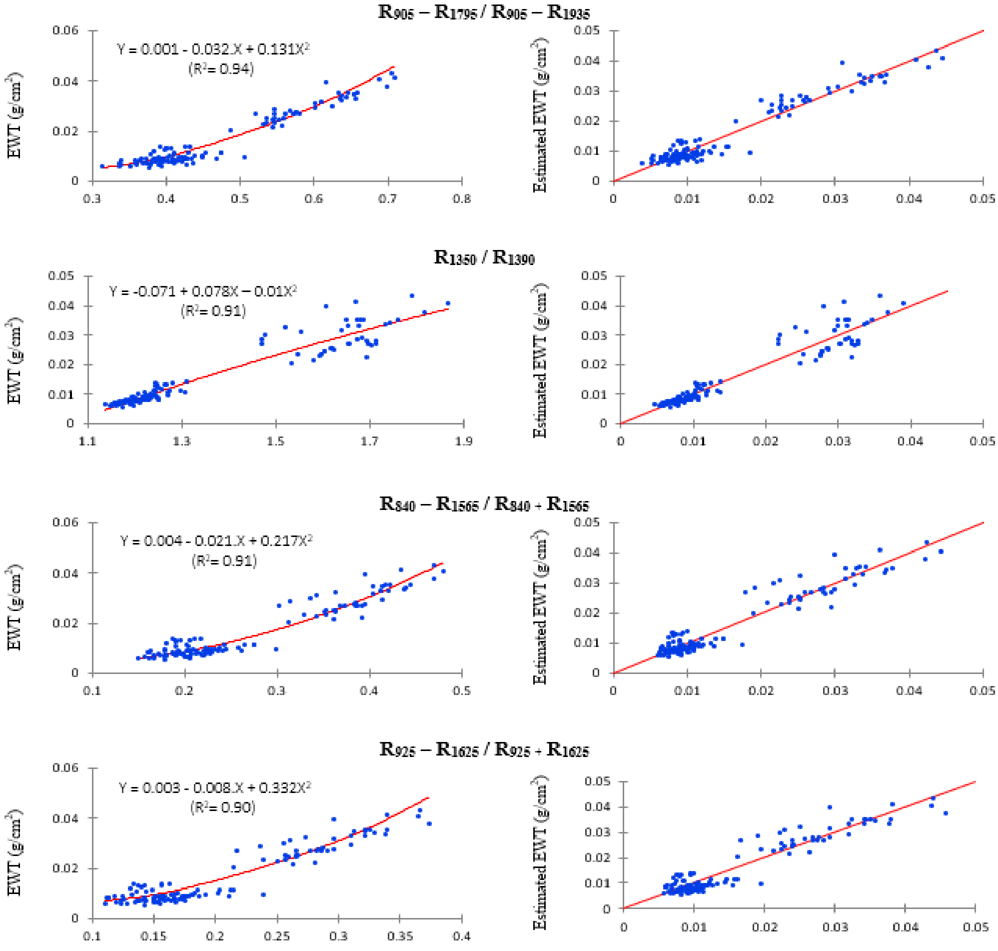

Figure 7: Regression between the indices suggested and EWT parameters.

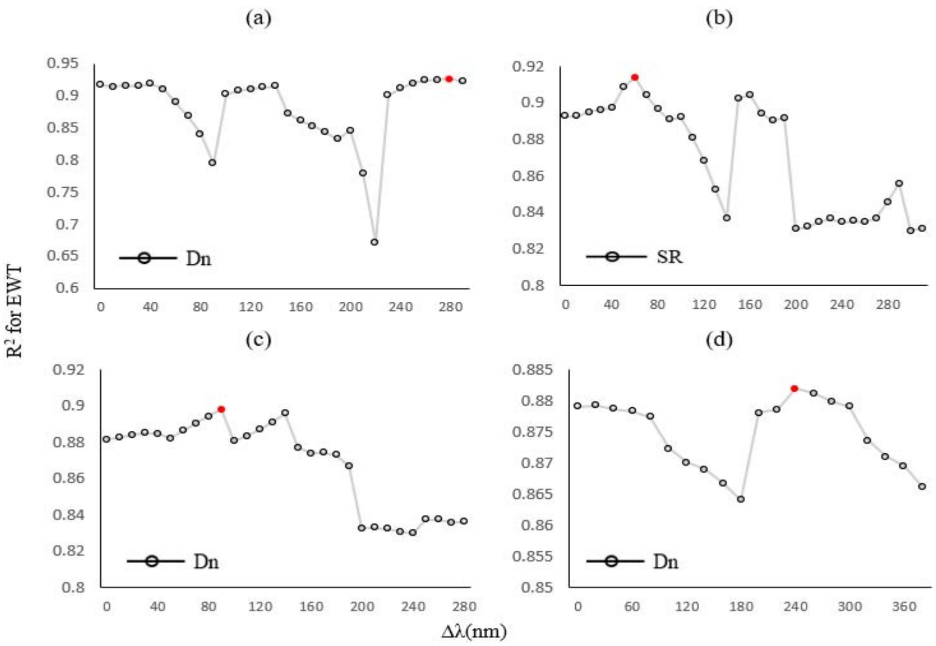

Figure 8: Suggested bandwidth indices for EWT with reliable stability.

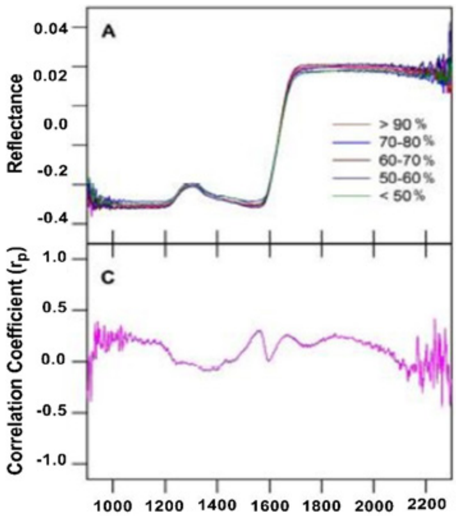

Figure 9: (A) Signatures of reflectance spectra, (B) reflectance first derivative (C) Correlation co-efficient (r_p) of relationship between equivalent water thickness (EWT; %) and reflectance spectra (D) first derivative of reflectance (coloured lines represented intervals of EWT).

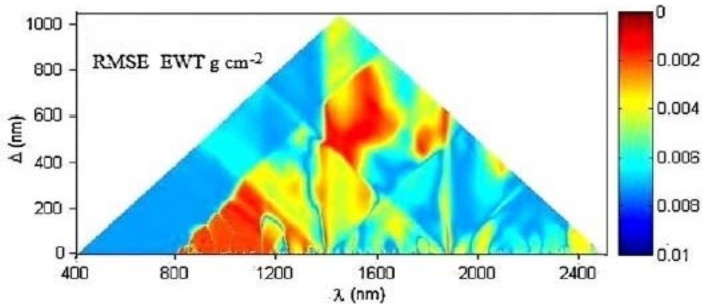

Figure 10: RMSE matrix of EWT using different indices with various combination of central wavelength (λ) and distance (Δ) based on data set. RMSE values are indicated in the legends on the right (Blue and red indicates large and small value respectively).

Conclusion

Using high-resolution data collection, we investigated the potential of estimating water content of leaves collected from research location. The electromagnetic spectrum part of the study reveals that the content of leaf water in the species is determined using high-resolution spectra. Knowledge of water stress is critical for making decisions related to irrigation and assessing drought in diverse plant groups.

In this research work, we have looked at how well certain hyperspectral indices performed while estimating EWT, PWC, GWCF and GWCD. With the best determination coefficient (R^2) and the lowest RMSE value, most spectral indices based on theory of water absorption performed exceptionally well in retrieving EWT for plant species. PWC, GWCF, and GWCD were not determined by the other water-sensitive indices since there is no position for LAI in these indices. As a result, it is assumed that EWT measured the water sensitive spectral indices instead of PWC and GWC. Variations in leaf pigeon and internal structure of leaf, on the other hand, are related with PWC and GWC and can result in visible and near-infrared reflectance changes.

The study focused on a set of near infrared spectral indices that we found in literature and after detailed analysis we found that four new indices were most sensitive to leaf water status in terms of EWT $(R_{905}-R_{1795})/(R_{1905}-R_{1935})$, R_{1350}/R_{1390}, $(R_{840}-R_{1565})/(R_{840}+R_{1565})$ and $(R_{925}-R_{1625})/(R_{925}+R_{1625})$ and also showed stability in both aspects. Leaf area index has a strong impact on the values of spectral leaf water indices, although it has limited impacts on other environmental variables. Recommended indices for leaf water content mapping appear to be the most promising. However, more research is needed to scale these water estimates connections to a wider scale and completely comprehend the leaf experiment process.

Researchers working on calculating EWT haven't paid much attention to specular reflection of the leaf surface in these directions, which has only a little impact on spectral reflection measurements. Another advantage of these indices is that they can be utilized with reflected signals from a range of plant species in different regions or country under varied measurement conditions. This is simply due to the fact that multi-angular reflectance factors of leaves include reflectance factors dominated by specular reflection from the leaf surface, in addition to comparable reflection values as those measured by leaf clip or integrating sphere.

Acknowledgment

Thanks to the school of Geographical sciences, Northeast Normal

Univesity, Changchun, China for collecting the data and using the required instruments.

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