OPTIMUM NARROW-BAND INDICES FOR ESTIMATION OF VEGETATION WATER CONTENT USING HYPERSPECTRAL REMOTE SENSING CONSIDERING SOIL BACKGROUND

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ABSTRACT: Developments in the field of hyperspectral remote sensing have provided the possibility of having new indices for estimation of vegetation biochemical and biophysical properties. Information about vegetation water content and water stress has widespread utility in agriculture, forestry and hydrology and support management of the natural resources. The objective of this study was first to explore sensitive spectral bands that are most suitable for estimation of vegetation water content and second to investigate if soil type affects in selecting the best narrow band index and optimum bands for them in estimation of vegetation water content. The study takes advantage of using a dataset collected during a controlled laboratory experiment. Water content was destructively acquired for four species with different leaf size and shape and different treatments. The spectral measurements have been carried out by using a GER spectroradiometer. Two groups of narrow band vegetation indices, namely ratio based and soil based were compared for estimating vegetation water content by using linear regression model. All two band combinations involving 584 wavelengths between 400 and 2400 nm were used for calculation of narrow band vegetation indices (RVI, NDWI, TSAVI and SAVI2).for pool (n=95), dark soil(n=48) and light soil (n=47) dataset. The predictive performances of hyperspectral indices were then determined and compared using cross validated R^2 and RMSE between measured and estimated water content.. However in pool data set, the selected narrow-band in all indices showed a high correlation in estimation of water content, highest correlation were observed for SAVI2 and RWI with water content. The coefficient of determination (R^2) between water content and optimum narrow band RWI, NDWI, SAVI2 and TSAVI using pool data set were 0.85, 0.81, 0.86, and 0.80 respectively. In soil type dataset, the RWI and NDWI were the best indices in light soil and RWI and SAVI2 in dark soil. The result indicates the better performance of narrowband SAVI2 almost in all data set. The least variation was depicted in SAVI2 when the soil type was changed. The result highlighted the role of background effect in selecting the best vegetation index and optimum spectral region for indices.

1. INTRODUCTION

Accurate estimate of vegetation parameters such as leaf pigments, nitrogen, dry matter, water content, and leaf area index (LAI) from remote sensing can assist in determining vegetation physiological status (Peñuelas, 1994) . Vegetation water content (VWC) can be recognized as an important parameter in agricultural and forestry applications (Jackson, 2003). Water stress in corps is usually detected only after it becomes visually apparent; this is often too late to prevent a reduction in crop yield (Dallon).Various methods have been used in estimating VWC in either statistical approaches (Chen, et al., 2005; Jackson, et al., 2003; Sims, et al., 2002), or physically based (canopy reflectance) models (Ceccato, et al., 2002; Ceccato, et al., 2002; zacro-Tejada, et al., 2004; Suárez, et al., 2008; Clevers, et al., 2010) . Water absorption bands are centered at 970, 1200, 1450 and 1950nm (Sims, et al., 2002; Clevers, et al., 2010) (Figure.1) and due to multiplicity of maximum water absorption region, a lot of different indices and techniques have been developed for estimation of vegetation water content (Jackson, et al., 2003; Chen, et al., 2005; Li, et al., 2006; Trombetti, et al., 2006; Clevers, et al., 2010; Ceccato, et al., 2002; Sims, et al., 2002). Spectral indices as a univariate statistical model are one of the most commonly used techniques for characterizing biophysical and biochemical vegetation variables. (Chen, et al., 2005; Gao, 1996; Ceccato, et al., 2002; Sims, et al., 2002).

A water vegetation index is typically a simple ratio utilizing data from two wavelengths: a wavelength where the water absorption coefficient is low as a reference band and a measurement wavelength where water absorption is moderate or high and the penetration depth into the canopy is maximized (Gao, 1996). In the past three dacades broad band indices have been widely used to estimation vegetation water content (Tucker, 1979; Peñuelas, 1994; Gao, 1996; Ceccato, et al., 2002). But broad band remote sensing products have limitations in providing accurate estimates of vegetation characteristics because of average spectral information over broad band widths (Cho, 2007). Also, The NIR and red-based indices such as NDVI are heavily influenced by soil background at low vegetation cover (Thenkabail, et al., 2000). Tucker (1997) used NDVI in red and NIR TM/ETM+ and AVHRR bands for estimation VWC. The limitation of using NDVI for estimating VWC is that RED and NIR are located in strong chlorophyll absorption region and high reflectance plateau of vegetation canopies respectively. Therefore, NDVI represents chlorophyll rather than water content (Chen, et al., 2005). A better way of estimating VWC is to use narrow band indices by computing all possible narrow bands. Resent development in hyperspectral remote sensing has provided additional bands for vegetation analysis within the visible, NIR and shortwave infrared (SWIR) (Cho, et al., 2007). Hyperspectral remote sensing with narrow and continuous bands is considered more sensitive to specific vegetation variables (Darvishzadeh, 2008). Researchers have shown that narrow band vegetation indices can be crucial for providing additional information with significant improvement over broad band vegetation indices in quantifying biophysical and biochemical vegetation characteristics (Thenkabail, et al., 2000; Broge, et al., 2001; Lee, et al., 2004; Darvishzadeha, et al., 2008). Numerous efforts have been done in improving the indices by determining optimal spectral bands and developing new indices to reduction soil background influences .Thus the main goal of this research is first: to evaluate the performance of various types of hyperspectral vegetation water content indices that contain ratio and soil based indices and second: improving them by choosing optimal bands .

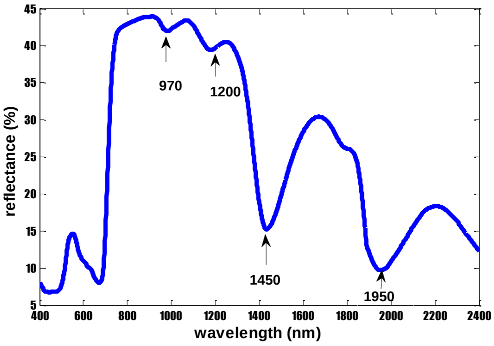

Figure 1: water absorption bands for a vegetation sample used in this study

2. DATA ANALYSIS

2.1 Laboratory Data collection

Four different plant species with different leaf shapes and sizes were indentified for sampling. In order to generate a wide variability within each species, we induced variation in canopy volume and background brightness (light and dark soil). To obtain differences in leaf optical properties such as water content, the plants were divided into two equal groups. One group was placed in a nutrient rich soil and the other group was placed in a very poor soil. Finally, a total of 95 plants were used for the study, 24 plants for each species (one sample was excluded). Water content was obtained by measuring wet/dry weight differences of each plant.

2.2 Canopy spectral measurements

Spectra were measured in a remote sensing laboratory with all walls and the ceiling coated with black material in order to avoid any ambient light or reflection. Eight replicates of canopy spectral measurements were taken from each subplot using a GER 3700 spectroradiometer (Geophysical and Environmental Research Corporation, Buffalo, New York) was used for the spectral measurements. The wavelength range is 350nm to 2500 nm with a spectral sampling of 1.5 nm in the 350-1050 nm rang, 6.2 nm in the 1050-1900nm rang and 9.5 nm in the 1900-2500 nm range. Spectral measurements of bare (and air-dried) soils were acquired each time before starting the canopy reflectance measurements of one group of species.

2.3 Preprocessing of spectra

Due to very high levels of noise, bands below 400 nm and 2400 nm were excluded. A moving Savitzky-Golay filter (Savitzky, et al., 1964) with a frame size of 17 data points were employed to smooth the spectra. The analysis and processing were carried out using MATLAB 7.8 (Mathwork, Inc).

3. METHODES

Four distinct types of narrow band indices were computed using 584 spectral wavelengths. The hyperspectral indices computed in this study were: (1) ratio-based indices involving Ratio Water Index (RWI) and Normalized Difference Water Index (NDWI) and (2) Soil- based indices involving Transformed Soil-Adjusted Vegetation Index (TSAVI) and Second Soil-Adjusted Vegetation Index (SAVI2) (Table1). Broad-band indices commonly calculated from two reflectance but hyperspectral data provide additional bands. The availability of hyperspectral data in 584 narrow bands allowed computation of 341056 combination for each one of the narrow band indices. As the retrieval of canopy biophysical variables is strongly affected by some factors such as background reflectance we divided the dataset into two dark and light group. Dark dataset relates to plants that located in dark soil and light dataset the plants in light soil. Then narrow band indices were computed for dark and light samples.

Table 1. Indices Used in This Study

Abbreviation	**Vegetation index name**	**Definition**	**Reference**
WI	Ratio water index	$\mathrm{WI} = \frac{R_{\lambda 1}}{R_{\lambda 2}}$	(Pearson, et al., 1972)
NDWI	Normalized difference water index	$\mathrm{NDWI} = \frac{R_{\lambda 1} - R_{\lambda 2}}{R_{\lambda 1} + R_{\lambda 2}}$	(Gao, 1996)
TSAVI	Transformed soil-adjusted vegetation index	$\mathrm{TSAVI} = \frac{a(R_{\lambda 1} - aR_{\lambda 2} - b)}{aR_{\lambda 1} + R_{\lambda 2} - ab}$	(Baret, et al., 1989)
SAVI2	Second soil-adjusted vegetation index	$\mathrm{SAVI2} = \frac{R_{\lambda 1}}{R_{\lambda 2} + (a/b)}$	(Major, et al., 1990)

3.1 Ratio based indices

Ratio water index (WI) is the simplest index based on two bands: first a reference reflectance where water doesn't absorb and another where water dose absorb (Sims, et al., 2002)(Eq.1).

$$WI = \frac{R_{\lambda 1}}{R_{\lambda 2}} \qquad (1)$$

The best WI we computed in this study were based on following equation:

$$WI = \frac{R_{723}}{R_{1418}} \qquad (2)$$

That R723 and R1418 were the reflectance at wavelengths 723 and 1418 respectively.
Another ratio vegetation index used in this study is Normalized Difference Vegetation Index (NDWI) developed by Gao (1996) for determination of VWC. This index is based on two wavelengths the NIR and SWIR. In this study the NDWI was defined as follows:

$$NDWI = \frac{R_{1965} - R_{697}}{R_{1965} + R_{697}} \qquad (3)$$

Usually NDWI are based on NIR and SWIR but in all band combination we found the best correlation in red and SWIR as shown in Eq.(3) Red is located in chlorophyll absorption band and in this wavelength water doesn't absorb then it is a good band for normalization of NDWI.

3.2 The soil-based indices

The soil-based indices require site-specific (a) and intercept (b). The soil line originally defined by Richardson and Weigand (1997) in a linear relationship between the NIR and Red reflectance of bare soil, and is defined by the slop and intercept of this line. However, there is also a "soil line" for other wavebands (Thenkabail, et al., 2000). In this study, the soil line parameters (a and b) were computed for all spectral measurement of 16 soil samples. The narrow band SAVI2 and TSAVI are computed according following equation respectively:

$$SAVI2 = \frac{R_{852}}{R_{1433} + (a/b)} \qquad (4)$$

$$TSAVI = \frac{a(R_{2135} - aR_{2273} - b)}{aR_{2135} + R_{2273} - ab} \qquad (5)$$

The optimal narrow band vegetation indices were determined using the coefficient of determination (R^2) of all possible two combinations band of vegetation index and VWC (the results are not shown) and then linear regression model was used to determine relationship between VWC and predictor variables. To validate regression model, Cross validation technique was used. In cross validation, each sample is estimated by the remaining samples. Cross validation can detect outliers (Schlerf, et al., 2005). By cross validation, for each regression variable we developed 95 individual models each time with 94 samples. The sample that was left out then was predicted by calibration model. (Darvishzadeha, et al., 2008). Then Cross validation R^2 and RMSE were computed using linear regression model for analyzing the performance of the narrow band indices (Table.2)

Table 2. Band position and R^2 values between narrow band VIs and VWC and performance of optimum narrow band indices for predicting VWC

VI	band positions of optimum narrow band indices and R^2			Performance of indices for predicting VWC	
	R^2	λ_1	λ_2	R^2_{cv}	RMSEcv
RWI	0.85	723	1418	0.84	0.36
NDWI	0.81	697	1965	0.79	0.41
SAVI2	0.86	852	1433	0.85	0.35
TSAVI	0.80	2135	2237	0. 78	0.42

4. RESULT AND DISSCUSION

The result of this study was inclusive with respect to if band selection in different vegetation water indices improve the correlation between VWC and indices and if the soil type affects on selection the best vegetation index. The best wavelength were detected using all possible tow band combination based on the coefficient of determination (R^2) between VWC and indices for pool data set and dark and light soil type as well (table2 and 3). Then linear regression analysis was employed to demonstrate the relationship between VWC and best narrow band indices for pool dataset and cross validation technique was used to validate the regression models and then The R^2cv and nRMSEcv of the regression also were computed (table 2, Figure.2).

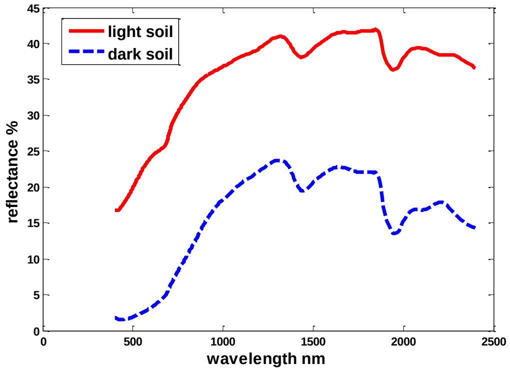

Figure 2. Differences in spectral reflectance due to light and dark soil foe sample with same amount of VWC

4.1 Estimating VWC by optimum narrow band indices using pool data

The best narrow bands for all indices are depicted in table 2. It can be observed from table 2 that narrow band RWI and SAVI2 showed the highest correlation with VWC (R^2RWI=o.85 & R^2SAVI2=0.86) although high correlation was observed for NDWI and TSAVI (R^2NDWI=0.81 & R^2TSAVI=0.8). In both RWI and SAVI2 the absorption band located close to 1440 nm (water absorption band), and another band is located in NIR region (723 & 852 nm) where water does not absorb. Between two narrow band soil adjustments SAVI2 performed better than TSAVI. The relationship between estimated and measured vegetation water content is illustrated in Figure.3, according to this figure all indices show good estimation of VWC but the highest accuracies are found for RWI and SAVI2. Comparison of the measured water content to the estimation VWC also demonstrate that saturation occurs for sample with high amount of VWC. Water band indices are not able to see all the water in a canopy because of saturation in high canopy water content. At high amount of VWC the amount of absorption band that can be absorb by leaves rapidly reaches a peak, in contrast, reflectance band continues to increase. As a result reflectance band continue to increase but absorption bands show only little decrease. Then only slight changes will occur in ratio.

4.2 Relation between VWC and indices based on dark and light soil dataset

Knowledge of background soil type is critical in understanding the role of soil type in selecting the best vegetation index and optimum narrow band of indices for estimating VWC. Reflectance spectra vary due to different brightness of background even with same amount of VWC (Figure.2). For considering background effects, narrow band indices were computed with data stratified according to soil type (dark and light data sets) for all possible two band combinations. Table.2 shows the selected optimum bands and coefficient of determination (R^2) between VIs and

VWC using dark and light soil samples. All of the four indices showed higher correlation over light soil than dark soil. SAVI2 had the least R^2 variation in two soil type (R^2dark=0.86 & R^2light=0.88) then it showed the lower sensitivity to variation that exist in background reflectance compared to other indices .So it can be a good choice when no information is available about crop background soil. The most variation was related to NDWI. Then in situation that the soil effect is high (like thin canopy) this VI is not a good selection. RWI and NDWI had better performance in estimating VWC in light soil and RWI and SAVI2 in dark soil. As it is shown in Table.3 in the two soil type the optimal narrow bands for the best indices are located in different spectral wavelength and this demonstrates that information about estimating VWC varies with soil type and by changing the background soil either the optimum bands or the best vegetation index alter.

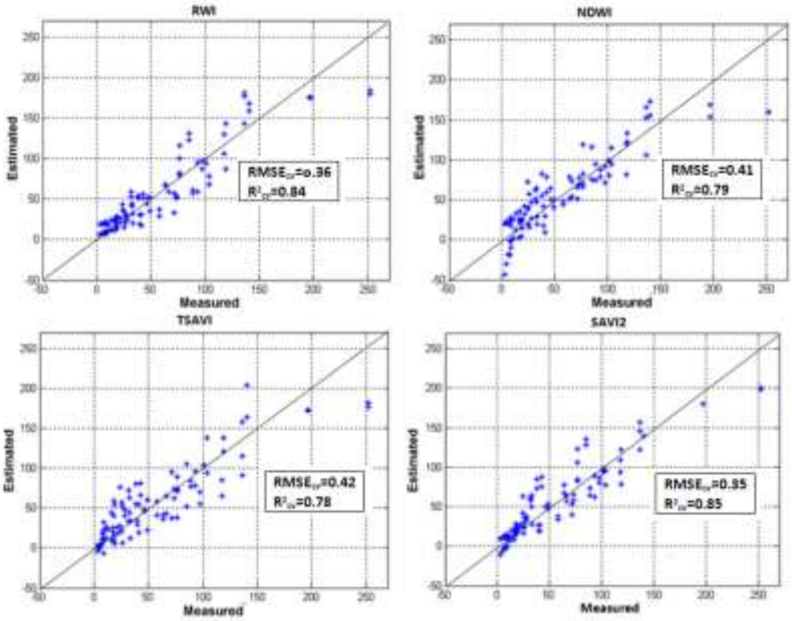

Figure 1. Linear regression analysis between indices and VWC for pool data set

Table 2 Band position and R^2 value between best narrow band indices and VWV in dark and light soil data set.

VI	Light soil			Dark soil		
	R^2	λ_1	λ_2	R^2	λ_1	λ_2
RWI	0.91	1858	1441	0.86	716	1965
NDWI	0.91	1943	589	0.85	2195	2165
SAVI2	0.88	1456	1441	0.86	529	1965
TSAVI	0.88	1456	1441	0.82	2225	2145

5. CONCLUSION

This research demonstrated the utility of different narrow band indices based on hyperspectral data for estimation vegetation water content (VWC), and applied different soil type (dark and light) to show the effect of background reflectance in selecting optimum narrow band index and optimal band in indices. The laboratory experiment allowed an assessment of the utility of all narrow wavelengths between 400nm to 2400nm in estimating VWC. In this study, the best selected bands for more indices were located near 1440, 1950 and 2200 nm. These regions, because of high molecular absorption of water vapor in atmosphere are avoided for remote sensing of the earth's science. The selected bands and the best vegetation index changed when the soil type altered. This indicates that the best narrow bands in different soil type are located in different spectral region and one index is not suitable for all situations. The result suggests the narrow band SAVI2 and RWI were the best for estimating VWC however NDWI and TSAVI also show good estimation. SAVI2 had lowest variation in different soil type.

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