UTILIZING THE VENμS RED-EDGE BANDS FOR ASSESSING LAI IN CROP FIELDS

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ABSTRACT:

This study aims to explore the potential and advantage of using the red-edge spectral bands of the forthcoming Vegetation and Environmental New micro Spacecraft (VENμS) for assessing Leaf Area Index (LAI) in field crops. Field spectral data were collected from experimental plots of wheat and potato at the northwestern Negev, Israel. These data were resampled to the VENμS bands being used for calculating the Red-Edge Inflection Point (REIP) and the Normalized Difference Vegetation Index (NDVI), which were compared to these same indices calculated with the original wavelengths. The VENμS data were found to be as good predictor of LAI as when using the original (continuous) data. The REIP was found to be significantly better than NDVI for prediction of wheat plants LAI and therefore could potentially be applied for future monitoring field crops LAI by VENμS.

1. INTRODUCTION

1.1 Leaf Area Index

Leaf Area Index (LAI) is defined as a simple ratio between the total one side leaf surface of a plant and the surface area of the land on which the plant grows. LAI is a dimensionless value, typically ranging from 0 for bare ground to 8 for dense vegetation. LAI is one of the most important variables governing the canopy processes (Baret et al., 1992) and is related to leaf and canopy chlorophyll contents, photosynthesis rate, carbon and nutrient cycles, dry and fresh biomass, and growing stages (Aparicio et al., 2002; Baret et al., 1992; Clevers et al., 2001; Coyne et al., 2009; Darvishzadeh et al., 2008; Pimstein et al., 2009; Pu et al., 2003; Ye et al., 2008). Hence, LAI is applied in plants and environmental studies of evaporation, transpiration, light absorption, yield estimation, growth stages of crops and chemical element cycling (Aparicio et al., 2002; Delegido et al., 2008; McCoy, 2005; Moran et al., 2004; Pimstein et al., 2009). Darvishzadeh (2008) that in addition to several direct and indirect methods, LAI has been estimated in numerous studies using remote sensing in either statistical approaches or canopy reflectance models, for agricultural crops as well as forests. A common non-destructive surrogate for LAI, which is based on reflectance of red (R) and near infrared (NIR) bands, is using the Normalized Difference Vegetation Index (NDVI). However, the prime disadvantage of this method is that the relationship between these two variables tends to saturate at LAI > 3 (Aparicio et al., 2002; Coyne et al., 2009), preventing to assess LAI in cases of high biomass loosing ability to monitor phenological stages that are important for decision making. Therefore, for better estimation of LAI, including higher LAI values, it is proposed to use red-edge inflection point (REIP).

1.2 Red-Edge

The red-edge region can be defined mathematically as the inflection point position on the slope connecting the reflectance in the red and in the NIR spectral regions (Mutanga and Skidmore, 2007; Pu et al., 2003). This steep increase of reflectance marks the transition between photosynthetically affected region of the spectrum (chlorophyll absorption feature in the red region), and the region with high reflectance values of the NIR plateau is affected by plant cell structure and leaves layers. This feature enables a clear representation of chlorophyll absorption dynamics, illustrating a shoulder shifts towards longer wavelengths when the absorption increases (chlorophyll content), and a shift towards the shorter wavelengths with decreasing absorption (Moran et al., 2004). Thus, the position of the red-edge, on canopy scale, provides an indication of plant condition that might be related to a variety of factors e.g., LAI, nutrients, water content, seasonal patterns, and canopy biomass (Blackburn and Steele, 1999; Clevers et al., 2001; Delegido et al., 2008; Jorgensen, 2002; Moran et al., 2004; Pu et al., 2003; Tarpley et al., 2000). Baret et al. (1992) modeled canopy scale reflectance using a radiative transfer model (SAIL model) concluding that information provided by shifts in the red-edge is not equivalent to broad bands R and NIR reflectance. They also concluded for canopy scale that shifts in red-edge are mainly produced by chlorophyll concentrations and LAI variations. The location of the REIP is also highly correlated with foliar chlorophyll content and dependant on the amount of chlorophyll observed by the sensor (Baret et al., 1992; Darvishzadeh et al., 2008). Clark et al. (1995) conducted experiment presenting red-edge shift detection obtained by the Airborne Visual and Infra-Red Imaging Spectrometer (AVIRIS) that is a hyperspectral airborne sensor. Multispectral or superspectral sensors that aim at high quality precision agricultural implementations should introduce unique combination of spectral and spatial resolutions as well as revisit time with the same viewing angle.

Due to the importance of the above-mentioned variables for vegetation monitoring in general, and for agriculture in particular, many spectral indices were derived to assess and correlate these variables with the state and condition of different crops. In recent years, most of the high spatial resolution operational satellites (e.g., Ikonos, QuickBird, RapidEye, GeoEye) are characterized by a small number of broad spectral bands, usually in the blue (B), green (G), R, and NIR. Due to their high spatial resolution, these systems are frequently applied for precision agriculture tasks. However, their spectral ability is limited mainly for simple broad-band vegetation indices. In this regard, it is important to mention that only one superspectral spaceborne system, MERIS, has 15 bands ranging from 390 to 1040 nm with programmable bandwidth ranging from 2.5 to 30 nm. The 4 red-edge bands are centered at 681.25, 708.75, 753.75 and 760.625 nm and commonly set to bandwidths of 7.5, 10, 7.5 and 3.75 nm, respectively. However, this system is characterized by spatial resolution of 300 m and therefore is not suitable for precision agriculture applications. The future superspectral satellite Sentinel-2, to be launched in 2013, is aiming at environmental applications. It will include 4 red-edge bands centered at 665, 705, 740 and 775 nm with bandwidth of 30, 15, 15 and 20 nm, and a spatial resolution of 10, 20, 20 and 20 m, respectively. This spatial resolution is still not enough for precision agricultural implementations.

1.3 Vegetation and Environmental New micro Spacecraft

Another future superspectral spaceborne system, named Vegetation and Environmental New micro Spacecraft (VENμS) will be launched in 2011. This system is characterized by high spatial (5.3 m), spectral (12 spectral bands in the visible – near infrared), and temporal (2 days revisit time) resolutions. In this regard, the most notable feature is the availability of four bands along the red-edge, centered at 667, 702, 742, and 782 nm with bandwidth of 30, 24, 16 and 16 respectively, as presented in Table 1. The satellite will circulate in a near polar sun-synchronous orbit at 720 km height and will acquire images with 27 km swath. The tilting capability, up to 30 degree along and across track, will provide more flexibility enabling to detect targets at up to 360 km off-nadir. All data for a given site will be acquired with the same observation angle in order to minimize directional effects. Due to these combined unique capabilities, the primary objective of this system is vegetation monitoring. Moreover, it will be specifically suitable for precision agriculture tasks such as site-specific management that can be applied in decision support systems. .

Band #	Band center (nm)	Bandwidth (nm)
1	420	40
2	443	40
3	490	40
4	555	40
5	620	40
6	620	40
7	667	30
8	702	24
9	742	16
10	782	16
11	865	40
12	910	20

Table 1. VENμS bands

1.4 Objectives

This study is strived to demonstrate the ability of the VENμS spectral bands to assess accurately LAI values in field crops. The first step is to find out if the spectral resolution of VENμS is appropriate for LAI assessment. Then the relation to LAI and its prediction abilities by the whole spectra as well as by REIP and NDVI, obtained by continuous spectra will be compared to the same analyses obtained by resampled VENμS data.

2. METHODOLOGY

The measurements acquired were ground spectral reflectance from canopy and the LAI of the plants included in the field of view of the spectral measurements. These were obtained in the north-west part of the Negev in Israel, for wheat and potato plants in experimental plots. The wheat measurements were conducted along two growing seasons, in the winters of 2003-04 (2004) and 2004-05 (2005), at Gilat Research Center (31° 21′ N, 34° 42′ E). The potato measurements were also conducted along two growing seasons in the autumn of 2006 and the spring of 2007, in experimental plots at Kibbutz Ruhama (31°28′ N, 34°41′ E).

The measurements in the wheat fields were obtained from around 20 days after emergence, until the heading stage around 90 days after emergence (Pimstein et al., 2007a). The measurements in the potato field were obtained from around 45 days after emergence, until around 90 days after emergence. 150 measurements were acquired in the 2004 season, 96 measurements in 2005, 120 measurements were obtained in the 2006 season and 100 measurements in the 2007. The total number of spectral measurements is 466. The data were analyzed by 7 different data sets: each growing season (e.g. 4 data sets); each crop (e.g. 2 data sets); and all the data together (e.g. 1 data set).

Each spectral measurement was followed by a LAI one. Canopy reflectance measurements were obtained using Analytical Spectral Devices (ASD) FieldSpec Pro FR spectrometer with a spectral range of 350-2500 nm, and 25° field of view. The spectral measurements were collected +/- 2 hours of solar noon, under clear skies in nadir orientation. The measurements were collected from 1.5 m above the ground, generating an instantaneous field of view of about 0.35 m^2. Along the season, as the height of the crops increased, the sensor's distance from the top of the canopy diminished from almost 1.5 m to 0.7 m for wheat canopy (Pimstein et al., 2007b) and to 0.9-1.3 m for potato canopy (Herrmann et al., In press). The height differences are corresponding to a field of view around 0.08 m^2 and 0.13-0.26 m^2, respectively. Pressed and smoothed powder of barium sulfate ($BaSO_4$) was used as a white reference (Hatchell, 1999) for the potato spectral data acquisition and the standard white reference panel (Spectralon Labsphere Inc.) for the wheat spectral data collection. The LAI was measured by the AccuPAR LP-80 device, that was programmed differently according to each crop and location based on the operation instructions (Decagon Devices, 2003). Each LAI value for data analysis is an average of three readings (replications). The three readings were collected from exactly the same location at which the canopy reflectance was measured.

The spectral data were resampled to VENμS spectral bands, being presented from now onwards as Continuous spectra and VENμS spectra, respectively. For both data formations, continuous and VENμS, the partial least squares (PLS) analysis was applied in order to find out the wavelengths and bands that are most influenced by LAI variation. Prediction by the root mean square error prediction (RMSEP) of LAI was calculated for the *continuous* as well as the *VENμS spectra*. Each of the 7 data sets was randomly sorted, and divided to 60% calibration and 40% validation. This prediction was implemented by The Unscrambler® software v.9.1. In order to know if there is any difference between pairs of correlation coefficient (r) values, the "difference tests" was applied using Statistica v.9 software. Two known vegetation indices values were calculated using both data formations, NDVI (Rouse et al., 1974) and REIP (Guyot and Baret, 1988). In formulas (1) and (2) the ρ stands for reflectance in certain wavelength (the center of the VENμS band) and expressed in nanometers.

$$\mathrm{NDVI} = \frac{\rho_{782} - \rho_{667}}{\rho_{782} + \rho_{667}} \tag{1}$$

$$\mathrm{REIP} = 700 + 40\{\frac{[(\rho_{667} + \rho_{782})/2] - \rho_{702}}{\rho_{738} - \rho_{702}}\} \tag{2}$$

The indices values were scatter plotted with LAI to provide general saturation examination as well as in order to obtain the correlation coefficient (r) values for linear relation between each of the indices and LAI. In order to apply prediction by the two indices each of the 7 data sets was randomly sorted, and divided to 60% calibration and 40% validation. LAI prediction by linear modeling was applied for both indices calculated by continuous as well as VENμS spectra the RMSEP was calculated in order to evaluate the prediction.

3. RESULTS AND DISCUSSION

Figure 1 presents the regression coefficient plots of the PLS model for all data. In this figure both Y axis values present the regression coefficients of VENμS spectra and continuous spectra. It is shown that both data formations have the same trend and that the red-edge region is highly influenced by LAI variability.

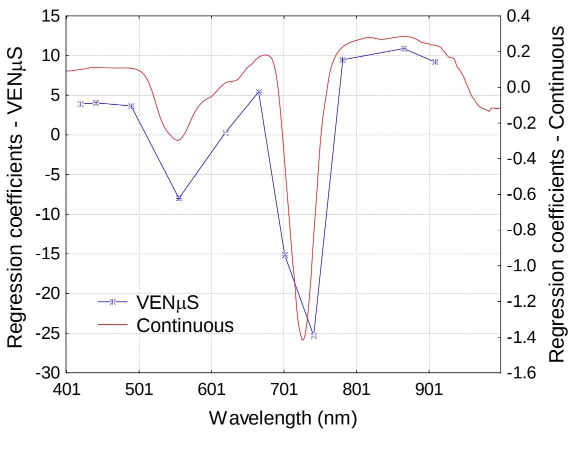

Figure 1. Figure 1. Regression coefficients of the continuous and VENμS spectra correlation with LAI (all data)

Table 2 presents the correlation coefficient (r) values of LAI predicted by both data formations for the entire spectra versus the observed LAI. All the r values are significant ($p<0.05$). According to the RMSEP values (Table 2) it can be concluded that the VENuS spectra can predict LAI as good as the continuous spectra. The probability (p) values of the data formation comparison intend to show similarity or dissimilarities between the data formations. Since all p values (except one case) are higher than 0.05, continuous spectra and VENuS spectra are with high probability the same in their abilities to predict LAI.

	VENμS		Continuous		Data formation comparison
	r	RMSEP	*r*	RMSEP	*p*
2007 potato	0.73	0.68	0.81	0.47	0.40
2006 potato	0.81	0.47	0.73	0.54	0.35
All potato	0.80	0.52	0.72	0.54	0.21
2005 wheat	0.73	0.82	0.80	0.82	0.49
2004 wheat	0.91	0.48	0.82	0.79	0.05
All wheat	0.93	0.68	0.95	0.60	0.24
All data	0.88	0.70	0.91	0.63	0.15

Table 2. LAI prediction by spectra for both data formations. All r values are significant ($p<0.05$).

As presented in Figures 2 and 3, saturation of the NDVI values and non saturation of the REIP values occurred as expected for the continuous and VENμS data formations, respectively. These figures present scatter plots of LAI relation to NDVI and REIP, for all 466 samples. Both data formations present saturation of NDVI when related to LAI. The saturation begins in LAI value of approximately 2 that is even smaller than what was expected according to the literature. However, NDVI can be an excellent LAI predictor up to LAI saturation, around LAI=2. Table 3 presents r values of relating NDVI and REIP to LAI for both data formations, all the r values are significant ($p<0.05$). It also presents p values of the r values of the same index being the same for both data formations as well as for both indices. For example – in the season (data set) of 2007 the probability that the r value of REIP calculated by VENμS data (0.70) is the same as the one calculated by continuous data (0.69) is 0.89. For the same season (data set) the probability that the r value of REIP (0.70) is the same as the r value of the NDVI (0.59), both calculated by VENμS data, is 0.24. Since, as presented in Table 3, the r values of the compared pairs are the same or their probability to be the same is very high VENμS spectra can provide the same quality of relation to LAI as the continuous spectra. When looking into the indices comparison it is shown that both data formations provide the same correlation abilities to LAI. The potato data sets (2007, 2006 and all potato) present p values higher than 0.05 for the indices comparison. Therefore, both data formations have high probability of having the same relation to LAI. For the other 4 data sets, the probabilities are smaller than 0.05, implying that NDVI and REIP r values are different. It is important to mention that in wheat and wheat and potato (2005, 2004, all wheat and all data) data sets the REIP r values are higher than the r values of the NDVI and therefore REIP is better related to LAI in both data formations.

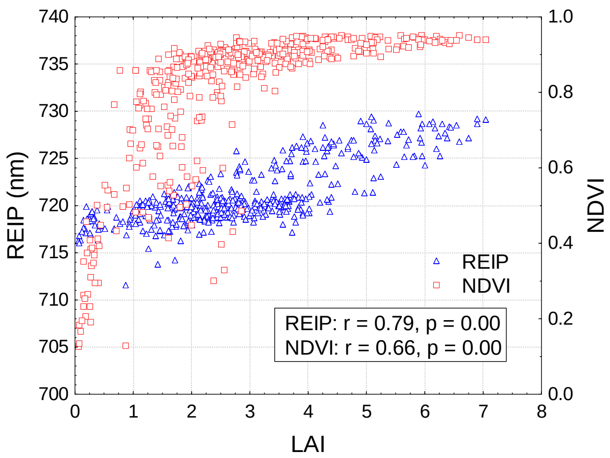

Figure 2. Relation of LAI to REIP and NDVI calculated by continuous spectra

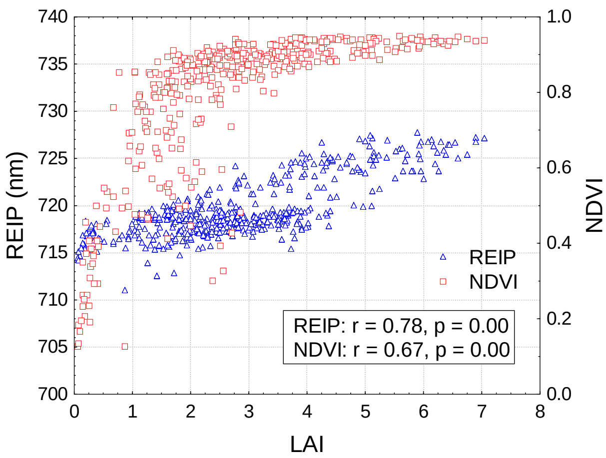

Figure 3. Relation of LAI to REIP and NDVI calculated by VENμS spectra

	VENμS		**Continuous**		**Data formation comparison**		**Indices comparison**	
	r		*r*		*p*		*p*	
	NDVI	**REIP**	**NDVI**	**REIP**	**NDVI**	**REIP**	**VENμS**	**Continuous**
2007 potato	0.59	0.70	0.60	0.69	0.91	0.89	0.24	0.19
2006 potato	0.55	0.54	0.55	0.55	1	0.91	0.83	1
All potato	0.57	0.62	0.57	0.63	1	0.86	0.42	0.42
2005 wheat	0.32	0.76	0.38	0.75	0.64	0.87	0.000	0.000
2004 wheat	0.71	0.84	0.71	0.85	1	0.76	0.005	0.002
All wheat	0.77	0.92	0.78	0.92	0.78	1	0.000	0.000
All data	0.67	0.78	0.66	0.79	0.79	0.69	0.000	0.000

Table 3. Correlation of NDVI and REIP indices to LAI and probability of difference; calibration data

	VENμS		**Continuous**		**VENμS**		**Continuous**		**Data formation comparison**		**Indices comparison**	
	r		*r*		RMSEP		RMSEP		*p*		*p*	
	NDVI	**REIP**	**NDVI**	**REIP**	**NDVI**	**REIP**	**NDVI**	**REIP**	**NDVI**	**REIP**	**VENμS**	**Continuous**
2007 potato	0.50	0.59	0.56	0.69	0.75	0.69	0.84	0.69	0.72	0.47	0.58	0.36
2006 potato	0.62	0.48	0.66	0.66	0.62	0.68	0.61	0.63	0.75	0.20	0.34	1
All potato	0.65	0.64	0.53	0.57	0.68	0.66	0.71	0.68	0.23	0.47	0.91	0.71
2005 wheat	0.36	0.72	0.49	0.84	1.15	0.85	1.31	0.79	0.51	0.20	0.03	0.006
2004 wheat	0.73	0.84	0.69	0.89	0.96	0.77	0.91	0.56	0.67	0.29	0.12	0.003
All wheat	0.77	0.93	0.77	0.93	1.14	0.67	1.21	0.74	1	1	0.000	0.000
All data	0.68	0.81	0.65	0.81	1.14	0.92	1.18	0.93	0.61	1	0.005	0.001

Table 4. LAI prediction by indices for both data formations; validation data

Table 4 presents r values of LAI predicted by NDVI and REIP, calculated by both data formations, versus the observed LAI, all the r values are significant ($p<0.05$). The RMSEP values of both data formations show advantage for the REIP, except for the case of data set 2006 by VENμS data. According to Table 4, for wheat, REIP has higher LAI prediction quality than NDVI. The p values of the data formation comparison are the probability that the r values of both data formations are the same. All p values of the data formation comparison are higher than 0.05, therefore the abilities of NDVI and REIP calculated by continuous and VENuS spectra to predict LAI are significantly the same for all 7 data sets. The indices comparison of p values shows the same behavior as in Table 2. Therefore, as mentioned before, the continuous data do not provide any significant advantage over the VENμS data. As observed in Table 2 for the last 4 data sets, REIP is a better predictor of LAI in both data formations, except for the 2004 data set in the case of VENμS resulting no difference between NDVI and REIP but for the other wheat data sets (2005 and all wheat) the REIP has significant advantage over the NDVI.

4. CONCLUSIONS

- Continuous and VENuS spectra as well as calculated indices relation to LAI and abilities to predict it are in most cases with high probability the same. The continuous data do not provide any robust or significant advantage over the VENμS resampled data. Therefore, in the spectral point of view the VENμS is as good as continuous data for LAI prediction.
- The red-edge is the most influenced area by LAI variability, the NDVI is saturated when related to LAI around 2, and for wheat REIP has significantly better relation and higher prediction accuracy to LAI than NDVI. Therefore the REIP is concluded to be a better index than NDVI for LAI assessment for wheat.
- Different crops presents different results therefore there is a need to explore more crops in order to explore the robustness of the results and also to obtain data from more seasons of wheat and potato in order to provide wider statistical basis.

5. SUMMERY

In order to demonstrate the ability of VENμS spectral bands to assess LAI values in field crops two spectral data formations (continuous and VENμS), for wheat and potato plants, were implemented. The relation of the data formations to LAI and prediction of it by entire spectra as well as by calculated indices (REIP and NDVI) were explored by several methods. The PLS analysis presented the red-edge as the most sensitive region to LAI variability and therefore the REIP was introduced to this study. Simple relation of the indices to LAI was also applied as well as prediction of LAI by the entire spectra as well as by indices. The results show that the superspectral band setting, as exists on the VENμS system, can perform as good as hyperspectral sensors in LAI prediction. For wheat the REIP is significantly a better predictor of LAI than the NDVI and therefore can by applied by VENμS for the same application.

The REIP calculated by VENμS data should be explored also for natural habitats in order to provide LAI assessment leading to productivity monitoring and potentially provide an additional environmental application for VENμS beside the potential agricultural application presented here.

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