ASSESSMENT OF FIELD CROPS LEAF AREA INDEX BY THE RED-EDGE INFLECTION POINT DERIVED FROM VENμS BANDS

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ABSTRACT

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

Keywords: Remote Sensing, Leaf Area Index, Red-edge inflection point, VENμS, Field crops.

INTRODUCTION

Leaf Area Index assessment

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. Hence LAI is a dimensionless value it is 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). Therefore, 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). LAI has been estimated in many studies using remote sensing techniques in either statistical approaches or canopy reflectance, for agricultural crops as well as forests and nevertheless further research of it is recommended (Aparicio et al., 2002; Asrar et al., 1984; Darvishzadeh et al., 2008; Gitelson, 2004; Kimura et al., 2004; Pimstein et al., 2009; Pu et al., 2003). A common non-destructive substitute for LAI, that is based on reflectance of red (R) and near infrared (NIR) bands, is 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 LAI assessment in cases of high biomass therefore loosing ability to monitor phenological stages that are important for decision making in agriculture. Therefore, for better estimation of LAI, including higher LAI values, it is proposed to use red-edge inflection point (REIP).

The red-edge can be defined mathematically as the inflection point position on the slope connecting the reflectance in the R 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 R region), and the NIR plateau with high reflectance values that is affected by plant cell structure and leaves layers. This feature enables a clear representation of the chlorophyll absorption dynamics, illustrating a shoulder shifts towards longer wavelengths when the chlorophyll content increase, and a shift towards the shorter wavelengths as the chlorophyll content decreases (Moran et al., 2004). 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), 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 short revisit time with the same viewing angle.

Vegetation and Environmental New micro Spacecraft

Many spectral indices were derived to assess and correlate monitoring vegetation variables with the 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 broad-band vegetation indices. In this regard, it is important to mention that the 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 that 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 most precision agricultural implementations. The CHRIS mode 4 provides 18 bands set to varying bandwidths of 6 to 11 nm. 13 bands are located in the red-edge region but the spatial resolution is 17 m.

Another future superspectral spaceborne system, named Vegetation and Environmental New micro Spacecraft (VENμS) will be launched in 2013. 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 with the same viewing angle) 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. 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 implemented in decision support systems.

Objectives

This study aims to explore the ability of the VENμS spectral bands to assess LAI values, in field crops, with comparison to continuous spectra. This primary objective is divided to specific objectives:

- To find if valid relation to LAI can be obtained by spectral resolution of VENμS.
- Explore the LAI prediction abilities of VENμS bands by the entire spectra as well as by REIP and NDVI.

METHODOLOGY

Field Work

The measurements acquired were ground canopy spectral reflectance 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, Israel, for wheat and potato plants in experimental plots. The wheat measurements were conducted during 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 during 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., 2007b). The measurements in the potato field were obtained from around 45 days after emergence, until around 90 days after emergence.

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., 2007a) 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.

Data Analysis

The total number of spectral measurements is 466; 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 data were organized and analyzed in 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 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.

The continuous spectral data were resampled to VENμS spectral bands, being presented from now onwards as continuous spectra and VENμS spectra, respectively. For both data formations, the partial least squares regression (PLSR) analysis was applied in order to find out the wavelengths and bands that are most influenced by LAI variation. Root mean square error of prediction (RMSEP) of LAI was calculated for the continuous as well as the VENμS spectra. 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, NDVI (Rouse et al., 1974) and REIP (Guyot and Baret, 1988), were calculated using both data formations. In Eqs. 1-2, ρ stands for reflectance in certain wavelength (the center of the VENμS band) and expressed in nanometers.

$$\mathrm{NDVI} = \frac{\rho_{782} - \rho_{667}}{\rho_{782} + \rho_{667}} \qquad (1)$$

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

The indices values were scatter plotted with LAI to provide saturation examination as well as in order to obtain the correlation coefficient (r) values for linear relation between each of the indices and LAI. LAI prediction by linear modeling was applied for both indices calculated by continuous as well as VENμS spectra, the RMSEP was used to evaluate the prediction.

RESULTS AND DISCUSSION

Regression coefficients of the PLSR model are shown (Fig. 1), for both VENμS and continuous spectra. It is shown that both data formations have the same trend. Furthermore, the red-edge region is the most influenced region by LAI variability and gets the highest absolute values, therefore its relation to LAI and prediction ability of this region will be farther explored.

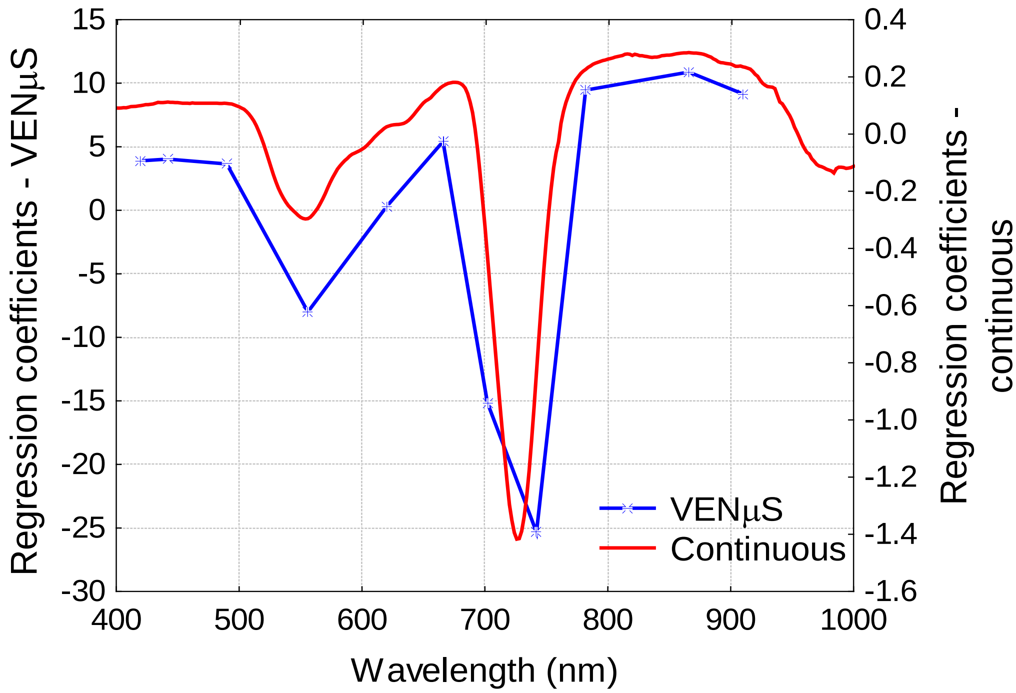

Fig. 1. Regression coefficients of the continuous and VENμS spectra correlation with LAI (all data)

Table 1 presents the correlation (r) values of predicted LAI, by both data formations for the entire spectra, versus the observed LAI. All r-values are significant ($p<0.05$). According to the RMSEP values in Table 1 the VENμS data can predict LAI as good as the continuous spectra. The probability (p) values of the data formation comparison show similarity or dissimilarity between the r values of both data formations. Since all p values (except one) are higher than 0.05, there is no significant difference in LAI prediction by continuous and or VENμS spectra.

Table 1. LAI prediction by entire continuous and VENμS spectra (466 samples). All r values are significant ($p<0.05$).

Data set	VENμS		Continuous		Data formation comparison
	r	RMSEP	r	RMSEP	Probability
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

Vegetation indices, as NDVI and REIP, can be used for crop estimation. As presented in Fig. 2, saturation of the NDVI values and non-saturation of the REIP values occurred as expected for both data formations. The saturation begins in LAI value of approximately 1.5 that is even smaller than what was expected according to the literature. However, NDVI can be an excellent LAI predictor up to the LAI saturation. In addition, a small difference exists between the values of each index calculated by continuous vs. VENμS spectra. This difference can be explained by the bias that exists for the REIP vs. almost no bias for the NDVI (Figs. 3 and 4). For both indices, there is a high correlation between indices calculated by continuous spectra and by VENμS spectra, $r^2=0.99$ and highly significant. Therefore NDVI and REIP calculated by VENμS spectra can perform as good as these calculated by continuous spectra.

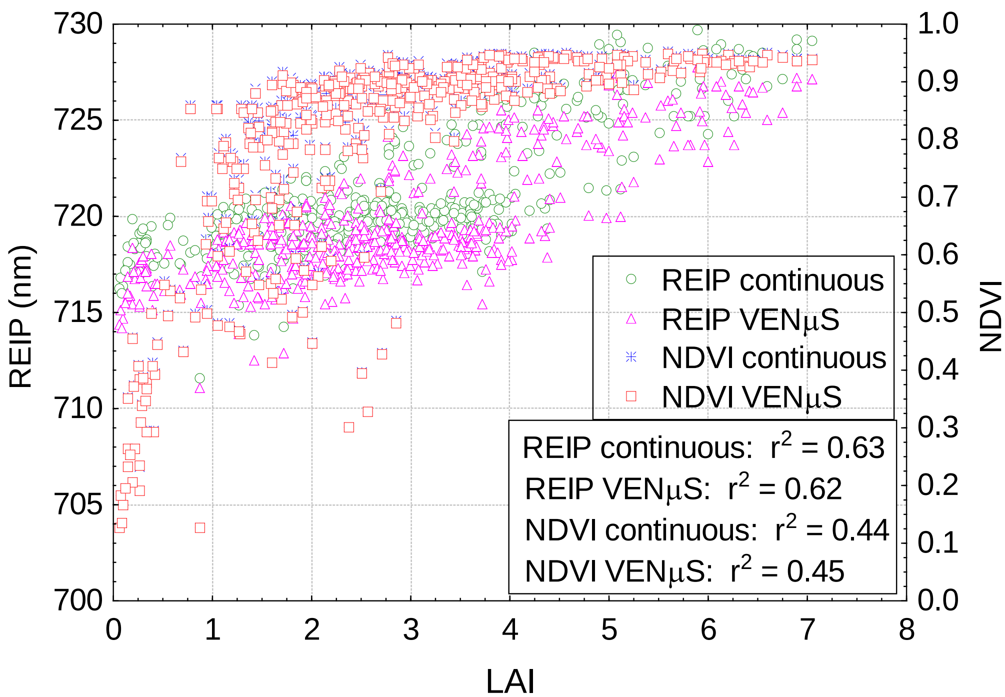

Fig. 2. Relation of LAI to REIP & NDVI calculated by both data formations (466 samples)

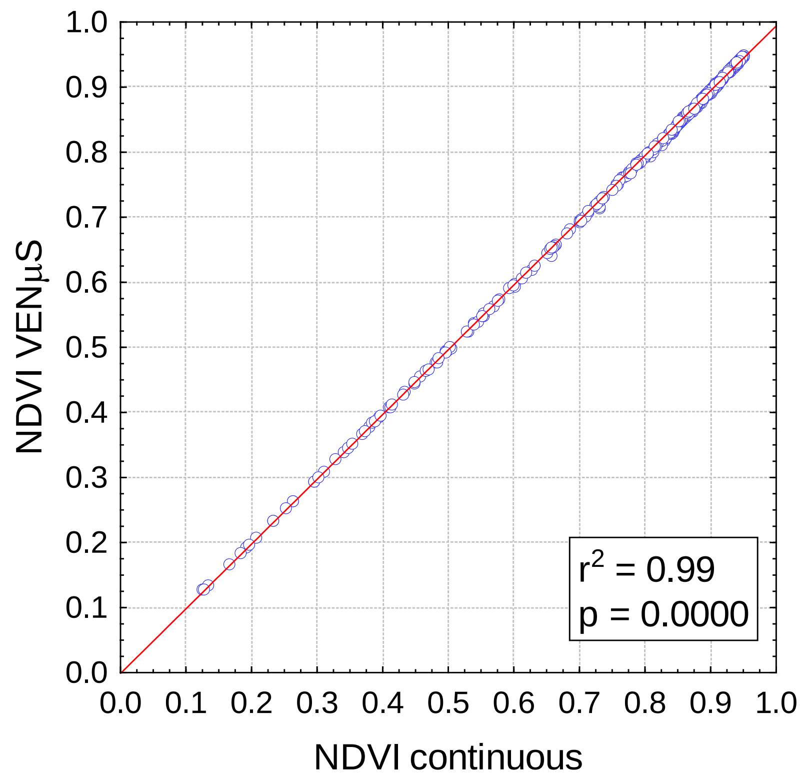

Fig. 3. Relation between NDVI calculated by both data formations

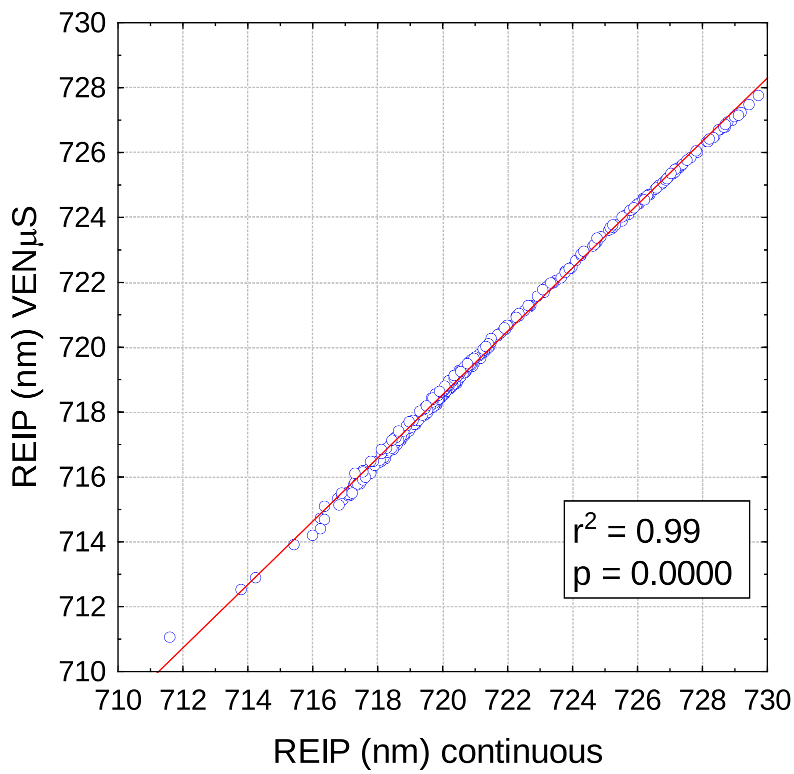

Fig. 4. Relation between REIP calculated by both data formations

In calibration data, all correlation (r-values) of NDVI and REIP to LAI were significant (Table 2; $p<0.05$), although some reach only low values (i.e. 2005 wheat data set by NDVI). It also presents the probability that 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 potato 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 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. The data formation comparison as well as the indices comparison results emphasize that VENμS spectra can provide the same quality of relation to LAI as the continuous spectra (Table 2). For the potato data sets (2007 potato, 2006 potato and all potato), no significant difference exists between NDVI and REIP. For the other data sets that include wheat samples (2005 wheat, 2004 wheat, all wheat and all data), the REIP has significant higher correlation with LAI than NDVI, in both data formations.

LAI prediction in the validation set exhibit similar level of correlation as shown by the calibration set, all the r-values are significant (Table 3; $p<0.05$). The RMSEP values of both data formations show advantage for the REIP, except for the case of data set 2006 potato by VENμS data. According to Table 3, for wheat, REIP has higher LAI prediction accuracy than NDVI. For potato, similar trend is shown in several sets, but it was not significant. Using the red-edge data to calculate the REIP and the importance of this region (Fig. 1) can explain the REIP advantage over the NDVI. Hence, it recommended using the red-edge data for LAI prediction. In addition, validation data sets, emphasize that VENμS multispectral data can be used for LAI prediction as well as hyperspectral continuous spectra data.

Table 2. Correlation of NDVI and REIP to LAI and probability of equality; calibration data

Data set	r				Probability			
	VENμS		Continuous		Data formation comparison		Indices comparison	
	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. LAI prediction by indices for both data formations and probability of equality; validation data

Data set	r				RMSEP				Probability			
	VENμS		Continuous		VENμS		Continuous		Data formation comparison		Indices comparison	
	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

SUMMARY AND CONCLUSIONS

In order to examine and evaluate the ability of VENμS spectral bands to assess LAI values in field crops two spectral data formations (continuous and VENμS), were compared. The relation of the data formations to LAI and prediction of it by spectra (continuous and VENμS) as well as by calculated indices (REIP and NDVI) were explored by several methods. The PLSR 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 the two indices. From the results it can be concluded:

- In the spectral point of view the VENμS spectra is as good as continuous spectra for LAI prediction.
- NDVI calculated by VENμS spectra is related to and can predict LAI as good as this calculated by continuous spectra.
- REIP calculated by VENμS spectra is related to and can predict LAI as good as this calculated by continuous spectra.
- REIP is a better LAI predictor than NDVI for the all wheat data set of this study.

Farther research should be done in order to find more crops suitable for LAI assessment and to establish the conclusions of this study. Additional study should be done also for environmental applications of VENμS spectra and REIP calculated by it to predict LAI in natural habitats.

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