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Research Article

Evaluation of Narrowband Indices for Rice Crop Parameter Retrieval and Discrimination between Different Nitrogen Treatments using Ground-based Hyperspectral Data

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ABSTRACT

A study was carried out in the experimental farm of the Central Potato Research Station (CPRS) in Jalandhar, Punjab to evaluate different narrowband/hyperspectral vegetation indices for retrieval of crop parameters. The study was carried out for Rice crop with five nitrogen fertiliser treatments (0,45,90,135,180 kg ha^{-1}), each treatment having four replications. Spectral reflectance was collected using handheld spectroradiometer. The indices computed for this purpose included: SR (Simple Ratio), NDVI (Normalized Difference Vegetation Index), SAVI (Soil Adjusted VI), OSAVI (Optimized SAVI), MSAVI2 (Modified SAVI2), MCARI (Modified Chlorophyll Absorption Ratio Index), TCARI (Transformed Chlorophyll Absorption Ratio Index), TCARI/OSAVI, NPCI (Normalized Pigments Chlorophyll ratio Index), ZTM (Zarco Tejada and Miller), $RE_{750\sim700}$ (Red edge Difference 750~700) and MCARI2 (Modified CARI2). Most of the narrowband indices in both dates of observation showed high (significant) correlation with crop parameters of rice. In order to avoid the impact of LAI on chlorophyll and vice-versa while computing correlation coefficients with the vegetation indices, partial correlation was computed. The partial correlations showed the relationships of the plant parameter with the VI, after removing the impact of the other influencing parameter. The total chlorophyll content was found to be highly significantly related to TCARI/OSAVI, NDVI and OSAVI. LAI was highly significantly related to SAVI, OSAVI, ZTM, $RE_{750\sim700}$ and MCARI2. Stepwise regression approach followed to determine the best-fit models for different rice crop parameters. The significant empirical equations derived from first date's observation were used to compute the crop parameters on second date. In case of all parameters (Total chlorophyll, Leaf nitrogen and LAI) the estimated values were significantly related to the actual values, with R^2 ranging from 0.61 to 0.74. Using the stepwise discriminant analysis (SDA), best set of indices was chosen for discrimination between the five nitrogen treatments. The indices chosen were TCARI/OSAVI and $RE_{750\sim700}$ for the first date and $RE_{750\sim700}$ and SR for the second date.

Key words: Hyperspectral, Narrowband indices, Rice crop, Leaf area index (LAI), Chlorophyll, Leaf nitrogen, Partial correlation, Stepwise discriminant analysis, Broadband indices

Introduction

Many agricultural activities need detailed information related to plant eco-physical variables and soil nutrient parameters. Estimating these

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parameters using conventional method is tedious and time consuming. Destructive tissue testing is a common way to assess crop N and P status (Osborne *et al*., 2002). Non-destructive technique for assessment of crop N, P and K status is presently needed. Remote sensing provides an alternative tool as a non-destructive technique for direct or indirect estimation of some these plant parameters.

In earth observation, over more than a decade, efforts have been made to investigate the applicability of multi spectral data and to improve geometric resolutions of optical sensors down to one meter. There is a need to have accurate, quantitative information of land surface parameters to understand the biogeophysical processes in terrestrial ecosystems. This calls for quantification of many parameters as well as inventory of a very different kind based upon spectral response in various wavelength regions. In this context, hyperspectral and ultraspectral remote sensing data has a crucial role to play.

Conventional remote sensing is based on the use of several rather broadly defined spectral regions, whereas hyperspectral remote sensing is based on the examination of many narrowly defined spectral channels (Campbell, 1996). Hyperspectral deals with imaging narrow spectral bands over a contiguous spectral range, and produce the spectra of all pixels in the scene. So a sensor with only 20 bands can also be hyperspectral when it covers the range from 500 to 700 nm with twenty 10-nm wide bands. Hyperspectral narrowband indices have been shown to be crucial for providing additional information with significant improvements over broadbands, in quantifying biophysical characteristics of agricultural crops, especially those related to crop phenology and stresses due to weeds, water and nitrogen. The reflectance and absorption features in narrow-bands are related to specific crop physico-chemical characteristics such as biochemical composition, physical structure, water content and plant ecophysical status (Strachan *et al*., 2002).

Narrowband vegetation indices

With availability of hyperspectral data, where reflectance at large number of spectral bands is available, many new vegetation indices have been developed (Table 1). These have been associated with absorption features of the various biochemical components of leaf/canopy. Gamon *et al.* (1992) reported that the commonly used broadband indices can be poor indicators of physiological changes at fine temporal scales under stress conditions because most physiological changes only produce changes at specific wavelengths of the reflectance pattern. The hyperspectral indices, used in this study are presented in Table 1. They can be divided into 3 categories. The first category includes the narrowband adaptation of common broadband indices, such as NDVI (Normalized difference vegetation index), SR (Simple ratio), SAVI (Soil adjusted vegetation index) and its different variations. SAVI, defined by Huete (1988) is less sensitive to soil reflectance at low LAI than NDVI. Numerous modifications of SAVI concept have been reported (Baret and Guyot, 1991). (Qi *et al.*, 1994) defined the modified SAVI (MSAVI) that replaced the constant L in the SAVI equation with a variable L function, such as: MSAVI = (1 + L)*(NIR - R) / (NIR + R + L), with L = 1 - 2a*NDVI*WDVI, where WDVI (= NIR-aR) is the weighted difference vegetation index (Clevers, 1988), and a is the slope of the soil line. With an iterative procedure they tried to improve MSAVI by minimizing the soil effects and finally arrived at MSAVI2. Rondeaux *et al.* (1996) showed that the value of L parameter is critical in the minimization of soil reflectance effects, and proposed the optimized SAVI (OSAVI) where L=0.16 was the optimized value. For computation of these indices, the wavelengths 670 nm in red and 800 nm in NIR region were used (Broge and Leblanc, 2000). However the optimum band for computation of the above indices can be selected based on the correlation curve spectral reflectance at all wavelengths and the biophysical parameter, which needs to be estimated (Ray *et al.*, 2006). The second category of indices is related to absorption features of pigments, most importantly the chlorophyll. Pigments are integrally related to the physiological function of leaves. Chlorophyll absorbs light energy and transfers it into the

Table 1. Narrowband/ hyperspectral Vegetation Indices used in the study

Index	Computation	Reference
	Structural indices	
NDVI (Normalized Difference Vegetation Index)	$(\rho_n - \rho_r)/(\rho_n + \rho_r)$	Rouse *et al*. (1973)
SR (Simple Ratio)	ρ_n / ρ_r	Birth & McVey (1968)
SAVI (Soil Adjusted Vegetation Index)	$(\rho_n - \rho_r)(1+L) / (\rho_n + \rho_r + L)$ where $L = 0.5$	Huete (1988)
MSAVI2 (Modified SAVI)	$\rho_n + 0.5 - ((\rho_n + 0.5)^2 - 2(\rho_n - \rho_r))^{0.5}$	Qi *et al*. (1994)
OSAVI (Optimized SAVI)	$(1+0.16)(\rho_{800} - \rho_{670})/(\rho_{800} + \rho_{670} + 0.16)$	Rondeaux *et al*. (1996).
	Chlorophyll/Pigment related indices	
MCARI (Modified Chlorophyll Absorption Ratio Index)	$MCARI = [(R_{700} - R_{670})\text{-}0.2(R_{700} - R_{550})](R_{700}/R_{670})$	Daughtry *et al*. (2000)
TCARI (Transformed CARI)	$TCARI = 3\,[(R_{700} - R_{670})\text{-}0.2(R_{700} - R_{550})(R_{700}/R_{670})]$	Haboudane *et al*. (2002)
NPCI (Normalized Pigment Chlorophyll Index)	$NPCI = (R_{680} - R_{430}) / (R_{680} + R_{430})$	Penuelas *et al*. (1995)
	Chlorophyll indices modified for LAI estimation	
MCARI2	$MCARI2 = 1.5\,[2.5\,(R_{800} - R_{670}) - 1.3\,(R_{800} - R_{550})]/ [(2\,R_{800} + 1)^2 - (6R_{800} - 5\,(R670)^{0.5}) - 0.5]$	Haboudane *et al*. (2004)
	Red edge indices	
Red Edge 750~700	$R_{750} - R_{700}$	Gitelson&Merzylak (1997)
ZTM (Zarco Tejada and Miller)	$ZTM = (R_{750} / R_{710})$	Zarco Tejada *et al*. (2001)

photosynthetic apparatus. The chlorophylls have strong absorbance peaks in the red and blue region of the spectrum. Since the blue peak overlaps with the absorbance of the carotenoids, it is not generally used for the estimation of chlorophyll content. Maximum absorbance in the red region occurs between 660-680 nm region however, the reflectance at these wavelengths has not proved useful for prediction of chlorophyll contents of the spectral indices based on these wavelengths (Sims and Gamon, 2002). Consequently, empirical models for prediction of chlorophyll content from reflectance are largely based on reflectance in the 550 or 700 nm regions where higher chlorophyll contents are required to saturate the absorptance (Buschman and Nagel, 1993, Datt, 1998, Lichtenthaler *et al.*, 1996). Kim *et al.* (1994) found that the ratio 550:700 nm reflectance is constant at the leaf level regardless of the difference in chlorophyll concentration and then proposed the Chlorophyll Absorption Ratio Index (CARI) to calculate chlorophyll concentration, which measures the depth of chlorophyll absorption at 670 nm relative to the green reflectance peak at 550 nm and the reflectance at 700 nm. The CARI was then simplified by Daughtry *et al.* (2000) to obtain the Modified chlorophyll Absorption Ratio Index (MCARI). Haboudane *et al.* (2004) modified MCARI to make it less sensitive chlorophyll effects, and more responsive to green LAI variations and more resistant to soil and atmospheric effects. The MCARI1 was produced to lower the chlorophyll sensitivity effects and MCARI2 was produced to reduce soil contamination effects by introducing soil adjustment factor. Penuelas *et al.* (1994) have developed an index called NPCI (Normalized Pigments Chlorophyll ratio Index, (R880-R430)/(R880+R430)), which is highly correlated to chlorophyll content. Since carotenoid absorption peaks overlap with that of chlorophyll, generally ratio of carotenoid to chlorophyll is estimated instead of absolute carotenoid. Such indices compare the reflectance of blue region with that of red region. The third category of indices is based on 'red edge'. The region of red-NIR transition has been shown to have high information content for vegetation spectra (Collins, 1978). This region commonly known as 'red edge' represents the region of abrupt change in leaf reflectance between 680 to 780 nm caused by the combined effects of strong chlorophyll absorption in the red wavelengths and high reflectance in the NIR wavelengths due to internal leaf scattering (Horler *et al.*, 1983). The importance of red edge has earlier been documented by many workers (Elvidge *et al.,* 1993; Elvidge and Chen, 1994). Daughtry *et al.* (2000) and Zhao *et al.* (2003) have also found the influence of N deficiency on red edge reflectance. The red edge position (REP), also known as the red edge inflection point (REIP), is defined as the wavelength around 720 nm at which the first derivative of the spectral reflectance curve reaches its maximum value (Liang, 2004). It has been demonstrated by many workers (Horler *et al.*, 1983; Vogelman *et al*., 1993) that the change red edge position is highly related foliar chlorophyll content and is also an indicator of vegetation condition. Vogelman *et al*. (1993) defined a ratio of reflectance at 740~720 nm, which was well correlated with variation in total chlorophyll content of leaf. Similarly Zarco-Tejada *et al*. (2001) and Gitelson and Merzylak (1997) defined ratios at red edge region for leaf chlorophyll estimation.

Apart from these indices, there are other two categories of indices, which include those based on the derivatives of reflectance spectra (Penuealas *et al*., 1994) and the indices developed after removing the continuum form the reflectance spectra (Koakly and Clark, 1999; Mutanga *et al*., 2003).

Leaf area index retrieval

Green leaf area index (LAI) is a key variable used by crop physiologists and modelers for estimating foliage cover, as well as forecasting crop growth and yield (Haboudane *et al*., 2004). Thus LAI estimation forms an integral part of precision agriculture, where yield mapping and crop growth modelling are carried out to understand the need for site-specific management. Because LAI is functionally linked to the canopy spectral reflectance, its retrieval from remote sensing data has prompted many investigations and studies in recent years (Haboudane *et al*., 2004). Spectral vegetation indices calculated as combinations of near infrared and red reflectances have shown to be well correlated with canopy such as green leaf area index (Elvidge & Chen, 1995). They observed that narrow-band indices had better accuracy than conventional broad-band indices for estimating LAI. Boegh *et al*. (2002) found a robust linear relationship between LAI and near-infrared (NIR) reflectance. The correlations between vegetation indices and L were also important, in particular, for the enhanced vegetation index. Equations describing the relationships between LAI and spectral indices vary in both mathematical forms (linear, exponential, power, inverse of exponential, etc.) and empirical coefficients, depending on the experiments, the indices used, and the vegetation type (Chen *et al*., 2002; Gilabert *et al*., 1996; Matsushita & Tamura, 2002; Qi *et al*., 2000). Haboudane *et al*. (2004) found exponential relation between LAI and vegetation indices, which might be due to the fact the ratio-based indices generally approach a saturation level with increasing biomass (Broge and Leblanc, 2000).

Leaf chlorophyll estimation

A plant's photosynthetic potential is directly proportional to the quantity of chlorophyll present in the leaf tissue. Spectral reflectance of vegetation in the visible (VIS) region of the electromagnetic spectrum is primarily governed by chlorophyll pigments (Thomas & Gausman, 1977). Remotely sensed measurements of this parameter can provide information about the status of the plant without the use of destructive tissue sampling (Schlemmer *et al*. 2005). Over several years, expanding research activities have focused on understanding the relationships between vegetation optical properties and photosynthetic pigments concentrations within green leaves tissues, namely chlorophyll *a*, chlorophyll *b* and carotenoids. Development within the field of hyperspectral remote sensing imaging sensors has allowed for new ways of monitoring plant growth and estimating potential photosynthetic productivity (Broge and Leblanc, 2000). Workers such as Penuelas *et al*. (1995) and Blackburn (1998) have suggested use of narrow-band reflectance indices - for the determination of the absolute and relative concentrations of chlorophyll *a*, chlorophyll *b,* and the carotenoids in plant leaves. Furthermore, the utility of spectral derivative approaches for quantifying plant pigments has been investigated at a variety of scales (e.g. Filella and Penuelas, 1994). Pinar and Curran (1996) and Filella and Penuelas (1994) showed the utility of the reflectance at red edge for chlorophyll estimation. Zhao *et al*. (2005a) showed that leaf chlorophyll was linearly correlated with not only the reflectance ratio of $R_{1075/735}$, but also the first derivatives of the reflectance in red edge centered at 730 or 740 nm. However, chlorophyll estimation at canopy level has been, many times, difficult, because optical indices developed for chlorophyll content estimation, using crop canopy reflected radiation, are responsive to other vegetation and environmental parameters like LAI and underlying soil reflectance (Daughtry *et al.*, 2000; Kim *et al*., 1994). To overcome this, Haboudane *et al*. (2002), using simulated data proposed an index, Transformed Chlorophyll Absorption in Reflectance Index/Optimized Soil-Adjusted Vegetation Index (TCARI/OSAVI) which was both very sensitive to chlorophyll content variations and very resistant to the variations of LAI and solar zenith angle.

Leaf nitrogen content

Nitrogen nutrient is one of major factors limiting crop yield. Although adequate supply of N to crops is fundamental to optimize crop yields, mismanagement of N, such as excessive N application, causes lodging and also results in contamination of groundwater (Jaynes *et al*. 2001). Therefore, efficient monitoring of plant N status and appropriate N fertilizer management are essential to balance the factors of increasing cost of N fertilizer, the demand by the crop, and the need to minimize environmental perturbations, especially water quality (Jaynes *et al*. 2001). One of the goals of the farm managers is to accurately detect plant N status and provide N fertilizer in a timely manner to improve yield, increase N use efficiency and profit and minimize N losses to the environments (Zhao *et al*. 2005b). Estimating nitrogen content of the plant, through laboratory methods, is cumbersome and time-consuming, thereby making it difficult for the nitrogen management during crop growth. Studies have documented that N status of field crops can be assessed using leaf or canopy spectral reflectance data (Blackmer *et al*. 1994; Hinzman *et al*., 1986; Walburg *et al*., 1982). Because the majority of leaf N is contained in chlorophyll molecules, there is a close link between leaf chlorophyll content and leaf N content (Yoder and Pettigrew-Crosby, 1995). However, N treatments result in the differences in leaf area index, biomass, foliage cover, and leaf chlorophyll content and hence contribute to the differences in canopy spectral reflectance observed. Boegh *et al*. (2002), analyzing Compact Airborne Spectral Imager (CASI) multi-spectral data found that the canopy nitrogen concentrations at vegetative period was significantly correlated with the spectral reflectance in the green and far-red wavebands. Tarpley *et al*. (2000) found that leaf reflectance ratios between wavebands in the red edge (700–716 nm) and a waveband in the very near infrared region (755–920 nm) provided good prediction of leaf N concentration in cotton. Read *et al*. (2002) showed through multiple linear regression analysis, that reflectance at 437, 610, and 689 nm in canopies were important in explaining the observed N-induced and seasonal variation in leaf N concentration. Xue *et al*. (2004) found that the ratio of NIR to green (R_{810}/R_{560}) was linearly related to total leaf N accumulation, independent of N level and growth stage. Zhao *et al*. (2005a) showed that leaf N concentrations were linearly correlated with not only the reflectance ratio of $R_{405/715}$, but also the first derivatives of the reflectance in red edge centered at 730 or 740 nm. The importance of leaf reflectance at two narrow ranges centred at 555 and 715 nm for study of N deficiency has been shown by many

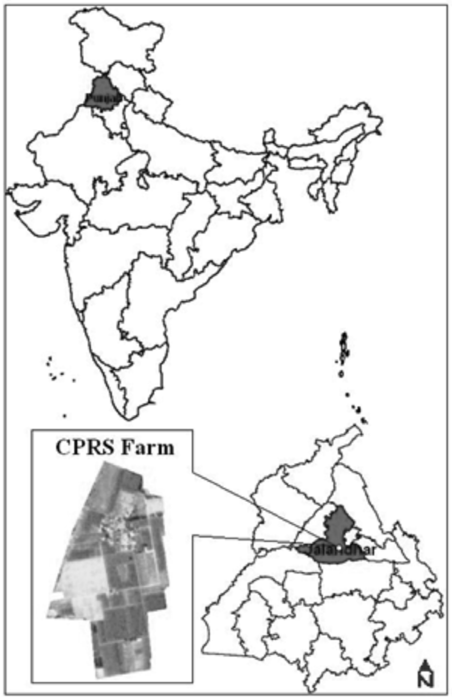

Fig. 1. Location map of Central Potato Research Station (CPRS) farm in Jalandhar

authors (Blackmer *et al*., 1994, Zhao *et al*. 2003, Zhao *et al*., 2005b). Jongschaap and Booij (2004) found an exponential relation between canopy organic nitrogen contents and red edge position derived from reflectance measurement.

Materials and Methods

Study Area

The study was carried in the experimental farm of the Central Potato Research Station (CPRS) in Jalandhar, Punjab, India (Fig. 1) located at 31.16°N latitude and 75.32°E longitude. The farm follows rice-potato-late wheat crop rotation. The growing period of rice, potato and late wheat are June-October, October–December and December–April, respectively. The average maximum temperature ranges from 18.8°C in January to 39.5° C in June. Similarly the minimum temperature ranges from 3.6° C in January to 25.3° C in June. The total annual rainfall is around 956 mm of which 80 per cent rainfall is received in four months from June to September, due to southeast monsoon. The soil type of the farm ranged from very deep sandy loam, very deep loam to very deep clay loam. The average values of surface soil parameters are presented in Table 2.

Experimental Plan

The experiment was conducted on rice crop in the year 2005-06 to study in detail the effect of nitrogen treatments on crop growth as perceived through hyperspectral reflectance. These treatments (Table 3) were also given to create the required variability in crop for developing reliable empirical models for parameter retrieval. Optimal irrigations were applied with uniform P and K fertilization as per the package of practices for the concerned crop. The plot size for each replication was 6×3 m^2. Half of the N dose and full dose of P and K were applied as basal does and rest of nitrogen was applied as top dressing.

Observations

The spectral reflectance was collected using a 512-channel spectroradiometer (Fieldspec®Pro, 2000) with a range of 325 to 1075 nm. Reflectance measurements were made about one

Table 2. Average values of surface soil parameters in CPRS Farm

O.C. (%)	Available N (ppm)	Available P (ppm)	Available K (ppm)	Sand (%)	Silt (%)	Clay (%)
0.45	113.41	22.17	159.48	74.09	14.44	11.46

Table 3. Experimental plan for rice crop in 2005-06 to study the effect of N fertilization

Crop	Nitrogen treatments	Replications	Variety	Date of Planting	Date of Harvest
Rice	5 (0,45,90,135,180 kg ha^{-1})	4	PR113	29th June	1st week of October

meter above the crop canopy with the sensor facing the crop and oriented normal to the plant. The reflectance measurements were collected for soil and crop using 25° FOV. The readings were taken on cloud free days at around solar noontime while taking the observations care was taken not to cast shadow over the area being scanned. A window based software View Spec Pro was used for viewing, analyzing and exporting the spectral data. The reflectance profile contained spectral wavelengths from 325 to 1075 nm with 1 nm interval. However, previous studies (Thenkabail *et al*., 2004, and Broge and Leblanc, 2000) have shown that wavebands in immediate neighborhood of one another provide similar information, hence becoming redundant. Given these facts, we have averaged the spectral data over 10 nm thus reducing the number of data points to 75 wavelengths. There are various methods to compress the data from 1 nm to 10 nm. However, we did simple averaging, assuming a square wave spectral response function within 10 nm range. We found that within any 10 nm range, the coefficient of variation of reflectance was less than 2 per cent. Hence an average can appropriately represent the reflectance values of that range. Leaf Area Index (LAI) was collected on the same day as that of the spectral data using Sunscan Canopy Analyser manufactured by Concord International. LAI is directly calculated by the analyser with the help of an array of 64 PAR sensors. The instrument has to be lowered to the ground level across the crop rows to collect data. It is connected to a Data Collection Terminal (DCT), which records the LAI reading. Three readings were taken from each plot. The leaf samples were collected on the same day of spectral observations for Nitrogen and chlorophyll content. Total N in plant leaf samples was estimated by Kjelhdal method (Gupta, 1999). On fresh representative leaf samples chlorophyll was extracted using the common N,N-dimethylformamide solvent method (Moran, 1992; Sadasivam and Manickam, 1992). Crop yield and biomass were measured at harvest. The chlorophyll reading was also measured using Minolta chlorophyll meter (model SPAD 502). This model has two light-emitting diodes, active at 650nm and 940nm. The chlorophyll content of a small section of the leaf is determined using the ratio of transmittance at 650nm, which is affected by leaf chlorophyll content, and transmittance of light at 940nm, which is not sensitive to chlorophyll content and serves as a reference. The output value of this equipment does not indicate the chlorophyll content directly, but is related to chlorophyll content. The SPAD (Soil Plant Analysis Development) reading which is also called chlorophyll content index (CCI) has been found to be significantly correlated with total foliar extractable chlorophyll for a number of agricultural species, For each plot the average reading of 10 plants, selected at random, were computed. Readings were taken on the fifth fully expanded leaf below the terminal of the plant.

These observations were collected two times during crop growth, i.e on 18th August (50 Days After Planting) and 5th September (68 DAP).

Parameter retrieval

The purpose of the study was to evaluate the utility of various narrowband indices for retrieval of crop parameters and discrimination between different nitrogen treatments. The indices computed for this purpose included: SR, NDVI, SAVI, OSAVI, MSAVI2, MCARI, TCARI, TCARI/OSAVI, NPCI, ZTM, $RE_{750\sim700}$ and MCARI2. The details about these indices are presented in Table 1. The statistical analysis carried out for this study included, the correlation of reflectance at different narrowbands with the crop parameters, computation of narrowband vegetation indices and correlation of vegetation indices with the crop parameters.

The optical indices developed for chlorophyll content estimation, using crop canopy reflected radiation, are responsive to other vegetation and environmental parameters like LAI and underlying soil reflectance (Daughtry *et al*., 2000; Kim *et al*., 1994). Similarly the indices for LAI estimation are responsive to changes in chlorophyll. This is because the chlorophyll content and the LAI were highly correlated as can be seen from Table 4. In order to reduce the effect of chlorophyll from LAI~VI relationships

Table 4. Correlation between different rice crop parameters

Parameters	Chl A	Chl B	Total Chl	SPAD	LAI	Leaf N
			18-August			
Chlorophyll A	1.000					
Chlorophyll B	0.989	1.000				
Total Chlorophyll	0.996	0.998	1.000			
SPAD Reading	0.800	0.841	0.827	1.000		
LAI	0.861	0.887	0.879	0.843	1.000	
Leaf N	0.852	0.885	0.875	0.814	0.950	1.000
			04-September			
Chlorophyll A	1.000					
Chlorophyll B	0.969	1.000				
Total Chlorophyll	0.989	0.995	1.000			
SPAD Reading	0.509	0.573	0.551	1.000		
LAI	0.536	0.551	0.549	0.831	1.000	
Leaf N	0.676	0.672	0.678	0.757	0.696	1.000

and the effect of LAI from chlorophyll~VI relationships partial correlation coefficients were computed. The partial correlations procedure computes partial correlation coefficients that describe the linear relationship between two variables while controlling for the effects of one or more additional variables. For the case of the partial correlation of VI on chlorophyll controlling for LAI, the bivariate regression of VI on LAI is performed, so that the residuals are the variance in VI after the effect of LAI is considered. The bivariate regression of chlorophyll on LAI is performed, so that the residuals are the variance in chlorophyll after the effect of LAI is considered. The residuals of VI are correlated with the residuals of chlorophyll, and this correlation is the partial correlation coefficient, $r_{VIChlorophyll.LAI}$.

The stepwise regression procedure was followed to find the empirical models for crop parameter estimation.

To get the best narrowband indices for crop discrimination under different nitrogen treatments, the stepwise discriminant analysis (SDA) was carried out. Wilks' Lambda is the test statistic preferred for Multivariate analysis of variance (MANOVA) and is found through a ratio of the determinants.

$$\Lambda = \frac{|S_{error}|}{|S_{effect}| + |S_{errror}|}$$

where, S is a matrix which is also known as sum of squares (SS) and cross-products, cross products or sum of products matrices. Wilks' Lambda is a multivariate test of significance, ranges between 0 to 1. The values close to 0 indicate the group means are different and values close to 1 indicate the group means are not different and 1 indicates all means are the same. The SDA was carried out using SPPS 11.5 (SPSS, 1999).

Broadband indices

In order to compare the prediction and discrimination power of the narrowband indices vis-à-vis broadband indices, five indices were selected. These indices were selected on the basis of the possibility of converting the narrowband into broadband data. These are also commonly used broadband indices. The narrowband reflectance was converted to the broadband reflectance using the spectral response function of IRS LISS III as follows (Liang, 2004).

$$R_b = \frac{\int_{l_{min}}^{l_{max}} R_l\, f(l)\, dl}{\int_{l_{min}}^{l_{max}} f(l)\, dl}$$

where R_b is the reflectance of broadband, λ is the wavelength and $f(\lambda)$ is the spectral response function.

Only, those narrowband indices, whose required wavelength were within the FWHM of IRS LISS III bands (Green: 520-590 nm, Red: 620-680 nm, NIR: 770-860 nm, SWIR: 1550-1700 nm) could be selected. Many of the indices like chlorophyll related indices, red edge based indices; derivative indices could not be selected for evaluation. The narrowband indices were computed using the reflectance of 680 and 770 nm with 3 nm bandwidth data. The spectral data of rice crop under different nitrogen treatments as observed on 68 DAP were used for this comparison. The evaluation was carried out for two aspects: predictive ability of rice crop parameters (chlorophyll, leaf N and LAI) and ability for discrimination between irrigation treatments.

Results and Discussion

Spectral Reflectance Profile

The average reflectance profile derived from handheld spectroradiometer for rice crop under different nitrogen treatments at two dates of observation are presented in Figure 2. In both the

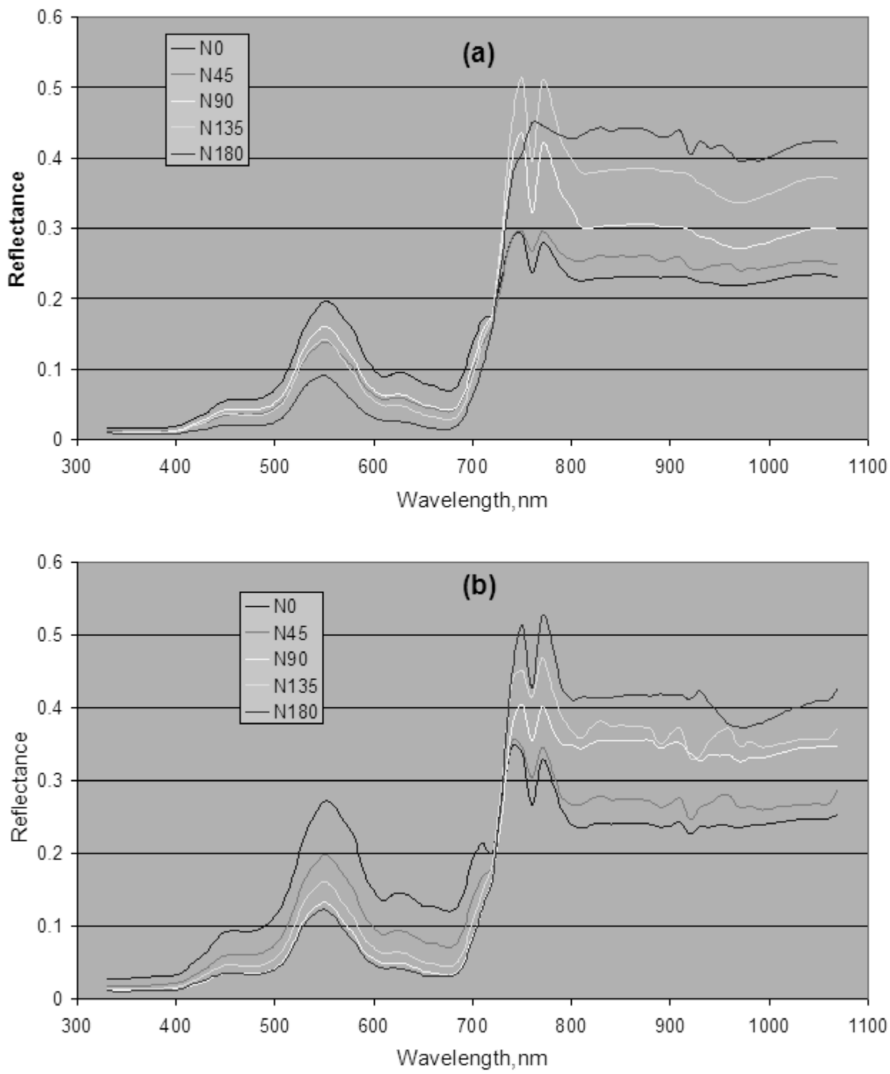

Fig. 2. The average spectral reflectance profile of rice crop under different nitrogen treatments: a) at 50 DAP, b) at 68 DAP

dates, the crops with high nitrogen treatment had high reflectance in visible region and low reflectance in NIR region compared to low nitrogen treated crops. The curves also showed that the difference between reflectance at NIR and red reduced as the nitrogen application rate declined.

N treatments resulted in the differences in leaf area index, biomass, foliage cover, and leaf chlorophyll content and hence contributed to the differences in canopy spectral reflectance. The dip in the reflectance curves near 760 nm is due to the existence of an O_2 absorption feature.

Relationship with indices

Most of the narrowband indices in both dates of observation showed high (significant) correlation with crop parameters of rice (Table 5). Among all the indices, a few typical chlorophyll indices like TCARI, TCARI/OSAVI and NPCI showed negative correlations with crop parameters. All other indices showed high positive correlation. Haboudane *et al*. (2002) also found negative correlation of chlorophyll and LAI with TCARI. The modification of TCARI to TCARI/OSAVI by Haboudane *et al*. (2002) for removing soil background effect has been found to be useful in our study. The correlation of TCARI/OSAVI with crop parameters was stronger than that of TCARI.

However, we found high correlations of chlorophyll with structural indices (NDVI, SR, SAVI and OSAVI) and high correlation of LAI with typical chlorophyll indices (NPCI, TCARI/OSAVI). This might be due to influence of one plant characteristic on other, as could be seen by

Table 5. Correlation of rice crop parameters with narrowband indices

Indices	Chlorophyll a	Chlorophyll b	Total chlorophyll	SPAD	LAI	Leaf N	Grain (q ha^{-1})
			50 DAP				
SR	0.731	0.714	0.723	0.436	0.752	0.747	0.682
NDVI	0.816	0.807	0.813	0.552	0.721	0.704	0.791
SAVI	0.826	0.810	0.818	0.550	0.754	0.747	0.800
OSAVI	0.824	0.811	0.818	0.553	0.742	0.730	0.799
MSAVI2	0.819	0.801	0.810	0.535	0.763	0.760	0.789
MCARI	0.462	0.450	0.456	0.219	0.543	0.539	0.458
TCARI	-0.529	-0.519	-0.524	-0.471	-0.378	-0.356	-0.545
TCARI/OSAVI	-0.819	-0.814	-0.818	-0.620	-0.705	-0.665	-0.809
NPCI	-0.771	-0.772	-0.773	-0.503	-0.779	-0.770	-0.718
ZTM	0.801	0.798	0.801	0.559	0.811	0.792	0.798
$RE_{750\sim700}$	0.808	0.805	0.809	0.618	0.825	0.793	0.849
MCARI2	0.799	0.782	0.790	0.501	0.767	0.768	0.755
			68 DAP				
SR	0.675	0.656	0.669	0.552	0.654	0.828	0.808
NDVI	0.794	0.781	0.792	0.650	0.715	0.657	0.856
SAVI	0.736	0.741	0.744	0.750	0.813	0.764	0.943
OSAVI	0.772	0.770	0.777	0.719	0.785	0.731	0.920
MSAVI2	0.714	0.720	0.723	0.738	0.807	0.793	0.943
MCARI	0.652	0.635	0.647	0.414	0.487	0.469	0.649
TCARI	-0.408	-0.368	-0.387	-0.025	-0.065	-0.378	-0.177
TCARI/OSAVI	-0.785	-0.787	-0.792	-0.637	-0.657	-0.649	-0.791
NPCI	-0.692	-0.677	-0.688	-0.736	-0.808	-0.825	-0.965
ZTM	0.634	0.634	0.638	0.794	0.857	0.844	0.957
$RE_{750\sim700}$	0.450	0.486	0.475	0.841	0.836	0.654	0.883
MCARI2	0.676	0.681	0.684	0.726	0.798	0.804	0.941

Table 6. Partial Correlation of rice chlorophyll and LAI with narrowband indices after removing the impact of LAI or total chlorophyll, respectively

Indices	Total chlorophyll (Controlling for LAI)	LAI (Controlling for total chlorophyll)
SR	0.509	0.461
NDVI	0.695**	0.548*
SAVI	0.609*	0.725**
OSAVI	0.671**	0.681**
MSAVI2	0.565*	0.710**
MCARI	0.530	0.206
TCARI	-0.443	0.192
TCARI/OSAVI	-0.670**	-0.436
NPCI	-0.520	-0.710**
ZTM	0.400	0.786**
$RE_{750\sim700}$	0.004	0.782**
MCARI2	0.487	0.693**

the high correlation between all plant characters in table 4. The improvement of MCARI to MCARI2, respectively by Haboudane *et al*. (2004), in order to make them better related to LAI, showed good result in our study. The correlation coefficient improved. Most of the indices showed higher correlation coefficient for chlorophyll contents (except for SPAD reading) on first date of observation than on second date. However, the grain yield was more related to the indices of the second date than those of first date.

Partial correlation coefficient

In order to avoid the impact of LAI on chlorophyll and vice-versa while computing correlation coefficients with the vegetation indices, partial correlation was computed. The partial correlations showed the relationships of the plant parameter with the VI, after removing the impact of the other influencing parameter. This analysis was carried out for the observation of the second date (Table 6). The correlation coefficient value reduced in all cases. The total chlorophyll content was found to be highly significantly related to TCARI/OSAVI, NDVI and OSAVI. It was no more significantly related the typical LAI index like MCARI2. LAI was highly significantly related structural indices like SAVI, OSAVI, red edge indices like ZTM, $RE_{750\sim700}$ and the typical LAI index like MCARI2. The correlation with TCARI/OSAVI reduced when the chlorophyll impact was removed. Among the indices, OSAVI was found to be the most useful in determining both the total chlorophyll content and LAI.

Empirical models for crop parameters

Stepwise regression approach followed to determine the best-fit models for different rice crop parameters. We could develop significant regression equations for total chlorophyll, SPAD reading, leaf nitrogen and LAI using data from first date's observation (Table 7). Among these the equation for SPAD had the lowest R^2 (0.385) and F (8.1) values, though it was also significant. For both leaf nitrogen and LAI, the red edge differences (750~700) could generate significant model, showing the utility of red edge. The importance of red edge has earlier been documented by many workers (Elvidge *et al*. 1993; Elvidge and Chen 1994). Daughtry *et al*. (2000) and Zhao *et al*. (2003) also found the influence of N deficiency on red edge reflectance. The OSAVI which had an optimized value of L for minimizing soil reflectance (Rondeaux *et al*., 1996) formed the significant regression equation with total chlorophyll.

Table 7. Empirical models for estimation of rice crop parameters from narrowband indices developed using stepwise regression technique at 50 DAP

Parameter	Model	R^2	N	F
Total chlorophyll	2.051+2.355*OSAVI	0.670	15	26.4**
SPAD	43.544 - 7.063*(TCARI/OSAVI)	0.385	15	8.1*
Leaf N	$1.188 + 2.833*RE_{750\sim700}$	0.629	15	27.8**
LAI	$0.117 + 2.919*RE_{750\sim700}$	0.681	15	22.0**

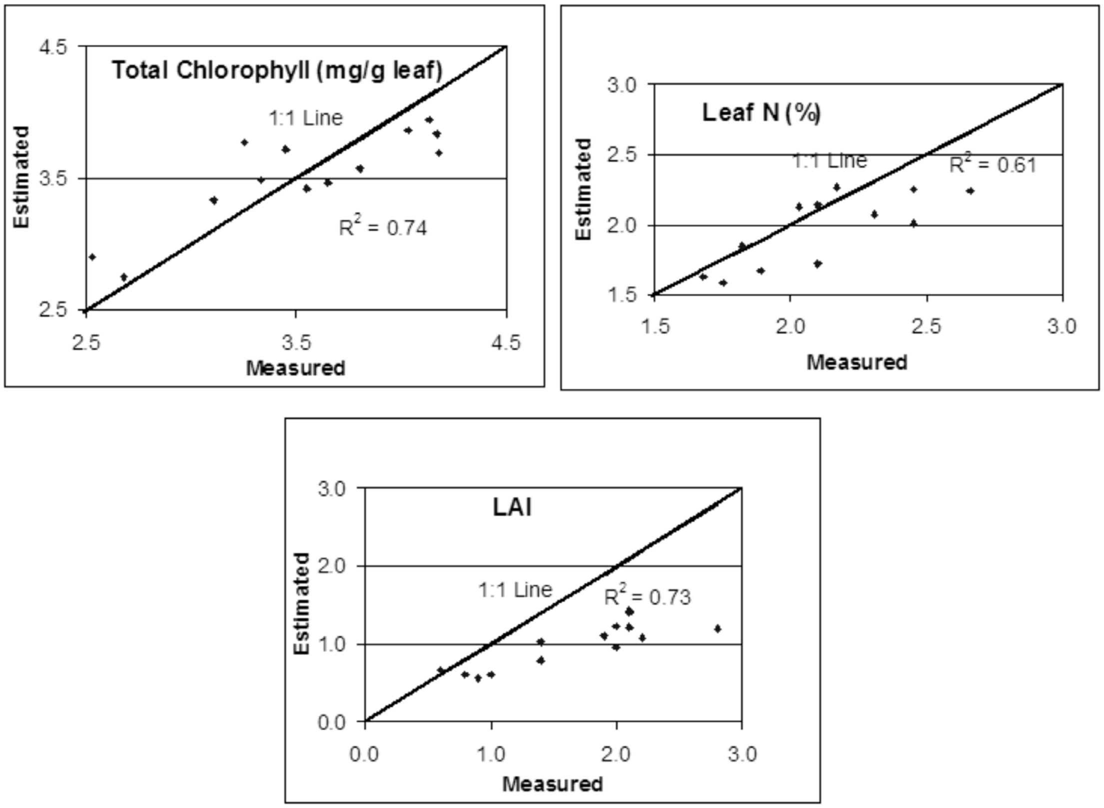

Fig. 3. Comparison between measured and estimated rice crop parameters

Estimation of Crop Parameters

The significant empirical equations derived from first observation date were used to compute the crop parameters on second date. These were compared with actual measured parameters (Fig. 3). In case of all parameters (Total chlorophyll, SPAD reading, leaf nitrogen and LAI) the estimated values were significantly related to the actual values, with R^2 ranging from 0.61 to 0.74. However, in case of total chlorophyll, the estimated values were higher than the actual values, while in case of LAI, the estimated values were much lower than the actual values.

Discrimination of nitrogen treatments

Using the stepwise discriminant analysis (SDA), best set of indices were chosen for discrimination between the five nitrogen treatments. The Wilks' Lambda and F value for each set is presented in Table 8. In this analysis, at each step, the variable (narrowband index) that minimizes the overall Wilks' Lambda was entered. High Wilks' lambda indicates less separability and high F value means more separability. The analysis stops when Wilks' Lambda gets saturated. The indices chosen were TCARI/OSAVI and $RE_{750\sim700}$ for the first date and $RE_{750\sim700}$ and SR for the second date. As mentioned earlier, the nitrogen treatments resulted in the differences in leaf area index, and also leaf chlorophyll content. Hence the indices which are

Table 8. Results of Stepwise Discriminant Analysis for separating impact of Nitrogen treatments on Rice crop

Step	Variables	Wilks' Lambda	F
	50 DAP		
1	TCARI/OSAVI	.065	36.2
2	TCARI/OSAVI, $RE_{750\sim700}$	.017	15.0
	68 DAP		
1	$RE_{750\sim700}$	.065	36.0
2	$RE_{750\sim700}$, SR	.009	21.4

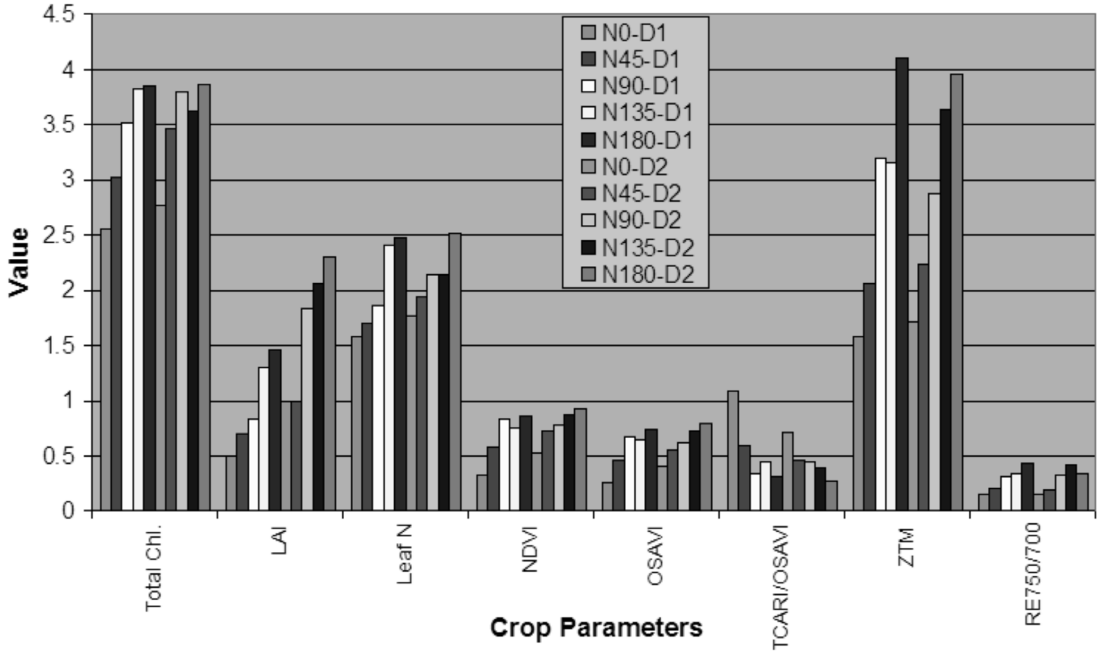

Fig. 4. Variation in rice crop parameters and spectral indices

related to both these parameters were efficient to discriminate between irrigation treatments. Table 6 showed that TCARI/OSAVI and $RE_{750\sim700}$ were significantly related to chlorophyll content and LAI, respectively. Hence these two indices were chosen in the SDA analysis.

Changes in vegetation indices

The variation in selected crop parameters and spectral indices with different treatments and on different dates of observation are presented in Figure 4. The differences in chlorophyll and leaf N content between the nitrogen treatments was less in 68 DAP compared 50 DAP. Though LAI increased from 50 DAP to 68 DAP, there was not much change in chlorophyll and nitrogen content. Except for TCARI/OSAVI, all other indices increased with increasing nitrogen fertilization and also form first to second date of observation. In all the narrowband indices, the treatment differences were pronounced on second date of observation than in first date of observation. This caused high F value in SDA analysis at 68 DAP, as can be seen in Table 8.

Relationship between narrowband and broad-band indices

The narrowband indices were highly correlated with the corresponding broadband indices with the correlation coefficient ranging from 0.978 to 0.999 (Table 9). The lowest correlation was for MCARI2. When the values

Table 9. Correlation coefficient between broadband and narrowband indices

Narrowband	Broadband Indices					
Indices	SR	NDVI	SAVI	OSAVI	MSAVI2	MCARI2
SR	0.999	0.836	0.890	0.876	0.919	0.951
NDVI	0.812	0.999	0.949	0.980	0.922	0.929
SAVI	0.867	0.953	0.998	0.990	0.990	0.971
OSAVI	0.854	0.983	0.990	0.998	0.974	0.965
MSAVI2	0.902	0.932	0.996	0.980	0.998	0.981
MCARI2	0.912	0.897	0.985	0.959	0.995	0.978

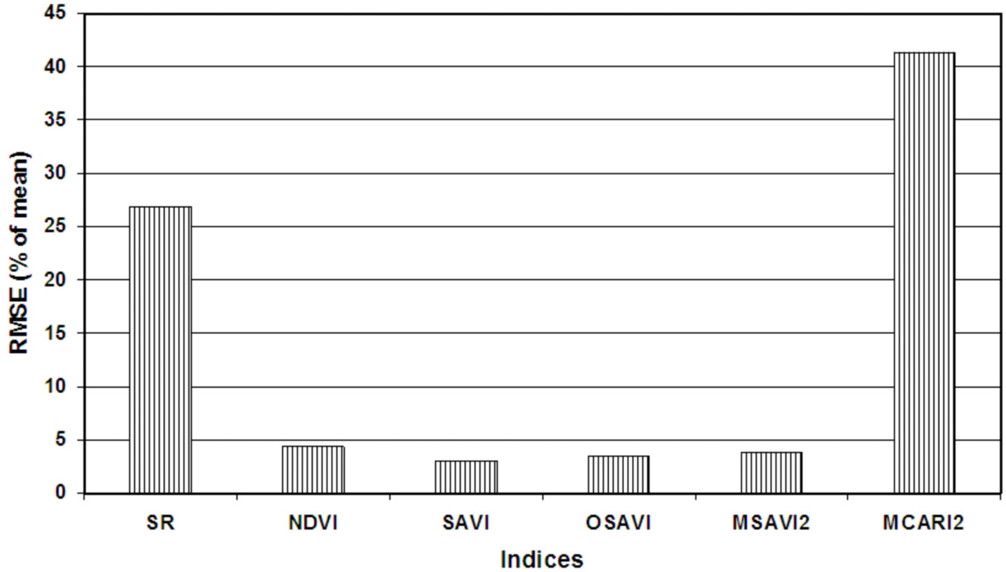

Fig. 5. RMSE (% of mean) between broadband and narrowband indices

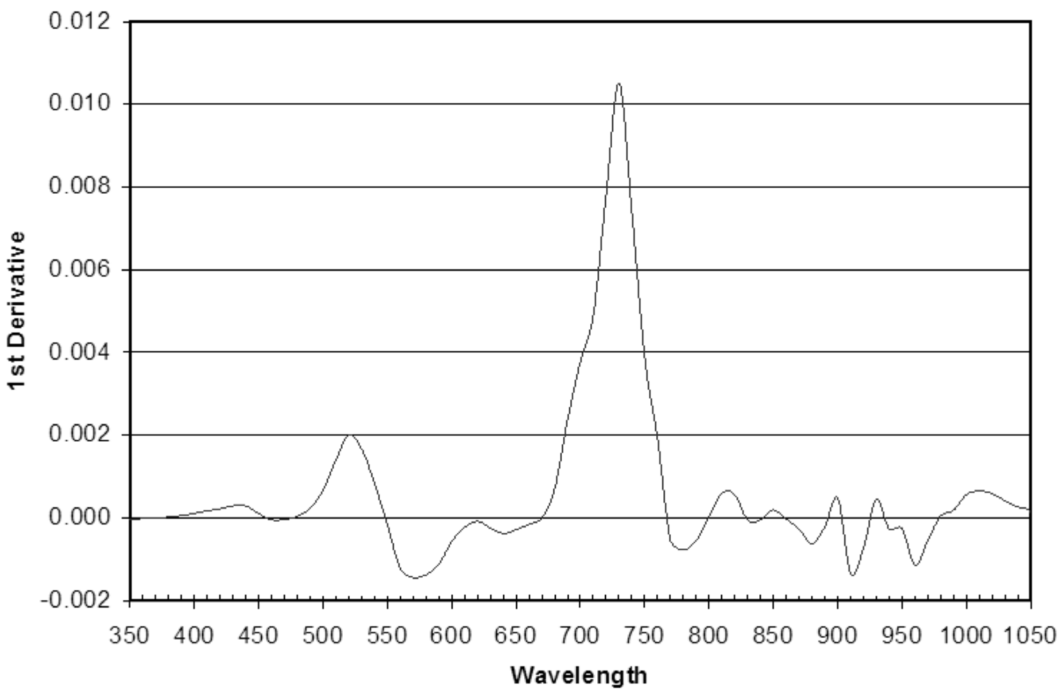

Fig. 6. First derivative spectra of rice crop at 68 DAP with N180 nitrogen treatment

were compared by computing RMSE (which was normalized with the mean), it was found that highest RMSE was in case of MCARI2, followed by SR (Fig. 5). NDVI and the SAVI based indices had < 5 per cent RMSE. These two analyses showed that there is not much difference between the broadband and narrowband versions of the conventional indices.

The reason for this is that the conventional indices are built on NIR (~800 nm) and red band (~680 nm). As can be seen from a typical first derivative spectrum (Fig. 6), there is not much change in the reflectance profile in this two wavelength region (low value of first derivative indicates low rate of change in the reflectance spectrum). However MACRI2, in its formulation,

Table 10. Correlation coefficient between crop parameters and indices

Crop	SR		NDVI		SAVI		OSAVI		MSAVI2		MCARI2	
Parameter	N*	B*	N	B	N	B	N	B	N	B	N	B
Total chlorophyll	0.67	0.67	0.79	0.79	0.74	0.74	0.78	0.78	0.72	0.72	0.68	0.75
SPAD	0.55	0.55	0.65	0.64	0.75	0.73	0.72	0.70	0.74	0.72	0.73	0.70
LAI	0.65	0.65	0.72	0.71	0.81	0.79	0.78	0.77	0.81	0.77	0.80	0.76
Leaf N	0.83	0.82	0.66	0.68	0.76	0.77	0.73	0.74	0.79	0.80	0.80	0.81

*N – Narrowband indices; B-Broadband indices

included the reflectance of 550 nm. There is steep change in the reflectance pattern around this wavelength (this includes the green peak), as can be seen from transition of value of 1st derivate from 0.002 to -0.002. Hence broadband index formed from this region would lose some information, and thus the RMSE was high.

Comparison of predictive ability of indices

The broadband and narrowband indices were correlated with plant parameters of rice, such as total chlorophyll, SPAD reading, LAI, leaf nitrogen and grain yield. In most of the cases there was no significant difference between the correlation coefficients of narrowband and broadband indices with plant parameter (Table 10). However in majority cases, the narrowband indices had slightly higher correlation coefficients than their broadband versions. For MCARI2 in three out of five cases narrowband indices had higher correlation coefficient.

Comparison of discrimination ability of indices

Analysis of variance (one way) was carried out to compare the ability of narrowband and broadband indices for discrimination between the five nitrogen treatments. Among the indices, MCARI2 had the highest ability for separation (as shown by the highest F value), followed by MSAVI2 (Table 11). Except for MSAVI2 three was not much difference in F value between broadband and narrowband version of any index. Narrow MCARI2 had a much higher F value than the broad MCARI2.

Table 11. F value of one way ANOVA for separation between irrigation treatments using broad and narrowband indices

Indices	Narrow	Broad
SR	16.94**	17.19**
NDVI	4.60*	4.97*
SAVI	14.10**	14.13**
OSAVI	8.76**	8.96**
MSAVI2	18.62**	18.06**
MCARI2	24.35**	13.32**

Conclusions

Retrieval of crop biophysical/biochemical parameters is important, not only for crop yield forecasting, but also for many important ecosystem process modeling and precision crop management.

It was found that for the conventional vegetation indices like NDVI, SAVI (and variations of SAVI), SR etc., which are based on red and NIR reflectance values, though there was no significant difference in the predictive and discriminative ability of the narrowband and broadband indices, in most cases the narrowband formulations performed better. Elvidge and Chen (1995) found that the narrow-band versions of the vegetation indices, like NDVI, PVI and SAVI had only slightly better accuracy than their broadband counterparts. But later Broge and Leblanc (2000) showed through simulation study that the classic broadband VIs were generally slightly better at predicting LAI and chlorophyll density than more recent narrowband indices. Our study showed that, among all the conventional indices, NDVI did not have much difference between narrowband and broadband formulation.

Narrowband indices were more related to leaf N content than broadband indices, where as for LAI there was not much difference.

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