USE OF HYPERSPECTRAL REMOTE SENSING DATA FOR CROP STRESS DETECTION: GROUND-BASED STUDIES

Shibendu Shankar Ray*, J. P. Singh[1] and Sushma Panigrahy

Space Applications Centre, ISRO, Ahmedabad, India
[1]Central Potato Research Station, Jalandhar, Punjab, India
*Email: ssray@sac.isro.gov.in

Commission VIII, WG VIII/6

KEYWORDS: Potato, Irrigation, Nitrogen, Disease, Hyperspectral, Narrowband indices,

ABSTRACT:

One of the major applications of hyperspectral data in agriculture is crop stress detection. It is essential to find the most optimum narrowbands and hyperspectral indices to discriminate between different levels of stresses. In this study, we have considered the nutrient stress, water stress and disease stress of potato crop. Additionally, we also included the discrimination between varieties, considering it as a genetic stress. Different sets of data were used for different stresses. While the observations for disease were collected from farmers' fields, the observations related to crop variety, nutrient (nitrogen) and water stress were collected from experimental fields in Punjab state of India. The field observations of reflectance were taken using ASD hand-held spectroradiometer (375-1075 nm). The optimum bands were selected based on Band-band R^2, Principal component analysis and discriminant analysis, respectively. Large number of narrowband vegetation indices was computed. The discriminant analysis was done to find out the best indices, which can differentiate potato varieties, nitrogen levels, irrigation levels and disease infestation. The study identified the nine bands, which best discriminate the potato varieties, nitrogen levels, irrigation levels and early late blight disease detection in potato. The wavebands selected in the study covered the green (520 and 560 nm), red (660 and 690 nm), red edge (730 nm) and NIR (760, 790 and 800 nm) region of the spectrum. Among the narrowband vegetation indices, the red edge indices performed best for separating variety, disease intensity, and nitrogen application rate. However, other indices like Triangular Vegetation Index and Simple Ratio performed well for discrimination between different irrigation treatments.

1. INTRODUCTION

Hyperspectral narrowbands are known to provide significant to dramatic improvements in information content when compared with broadbands in discrimination of land cover types (Janetos and Justice, 2000), detecting plant stress (Carter, 1994), identifying small differences in percent green vegetation cover (McGwire et al., 2000) and crop moisture variations (Peñuelas et al., 1995). The narrow bands are able to measure the exact characteristic absorption peaks of plant pigments and thereby provide better information related to plant health (Zhang et al., 2003).

Reflected light in specific visible, near- and middle-infrared regions of the electromagnetic spectrum have proved useful in detection of nutrient deficiencies, disease, and weed and insect infestations (Hatfield and Pinter 1993). However, when disease and physiological stresses directly affect the reflectance properties of individual leaves, the most pronounced initial changes often occur in the visible spectral region rather than in the infrared because of the sensitivity of chlorophyll to physiological disturbances (Knipling, 1970). Multi-spectral remote sensing data available from space-based and airborne sensors have shown the feasibility of discriminating damaged crops fields from the healthy ones (Pozdnyakova et al. 2002; Qin and Zhang 2005). Quantitative analysis of remote sensing data for diseased crop identification has not been extensively studied, in spite of being a potential application of remote sensing to crop disease control (Zhihao and Zhang, 2005). Use of Hyperspectral data for plant disease study is rather at a very nascent phase (Zhang et al., 2003).

Hyperspectral data from various sources provide canopy reflectance in large number of contiguous narrowbands. However, analysis of large number of bands, available with any hyperspectral sensor, is complex and time consuming. Thereby various attempts have been made to select optimum set of narrowbands for crop discrimination (Thenkabail, 2002, Thenkabail *et al*., 2004). Many methods have been used for discrimination of crops under different conditions, such as, reflectance from individual narrowbands (Mariotti et al., 1996), various ratio indices (Lyon et al., 1998, Carter, 1994), derivatives of reflectance spectra (Ray et al., 2006), and multi-variate statistical analysis (Thenkabail et al. 2004). Discriminant analysis has shown great potential for separating out fertilizer and irrigation application rates and eventually to identify areas of the canopy that are under ecophysiological stress from various sources (Strachan et al., 2002). It has been used successfully at both leaf (Penuelas et al., 1994) and canopy (Filella et al., 1995) levels. Apan et al. (2004) used a multiple discriminant function analysis (also called canonical discriminant analysis) with a stepwise selection method for discriminating of sugarcane disease.

Two major techniques for feature reduction in hyperspectral data are, the Principal Component Analysis (PCA) and the Stepwise discriminant analysis (SDA). The PCA tries to derive a new set of uncorrelated (orthogonal) variables, thereby reducing the number of variables. PCA attempts to identify underlying variables, or factors, that explain the pattern of correlations within a set of observed variables. PCA is often used in data reduction to identify a small number of factors that explain most of the variance observed in a much larger number of manifest variables. SDA, a procedure that reduces the data set to those variables that maximize between statistical group variability while minimizing within group variability, has also been used successfully to reduce the number of wavelength variables (data dimensionality). PCA is different from SDA in the sense that, in the former new vector variables that define the axes of greatest variability in the data are created, while in the latter the original variables that best describe differences between given groups are identified.

Strachan et al. (2002) taking reflectance measurements nine times during crop growth found that though individual reflectance-based indices demonstrated the relative differences between application rates and identified both nitrogen and water stresses at various times in the growing season, no single index was able to describe the status of the corn crop throughout the season..

It is essential to find the most optimum narrowbands and hyperspectral indices to discriminate between different levels of stresses. In this we have considered the nutrient stress, water stress and disease stress. We also included the discrimination between varieties, considering it as a genetic stress.

2. METHODOLOGY

2.1 Observation Details

The study was conducted on potato crop. Different sets of data were used for different stresses. The field observations of reflectance were taken using ASD hand-held spectroradiometer operating in a range of 375-1075 nm (FieldSpec®Pro, 2000). The detail procedures of observation are described by Jain et al. (2007)

For study of the disease, village Nijjarpura (31°34’29” N and 75°01’00”E) in district Amritsar of Punjab state in India was the study area. The observations on late blight of potato were recorded on 14th December, 2004 in a single large potato field affected with late blight in nature at around 60 day of crop-growth. Crops were at the same stage of development in the field during the observation. Variable late blight infected areas from the highly affected to the disease free crop could be located in the same field. The infestation was categorized into various levels using the Blight Measuring Scale (BMS), which is based on the percentage plant area affected by late blight (Anonymous 1947). Patches of crop canopy exhibiting 0, 0.1, 10, 25, 50, 75, 90 and 98 per cent foliage affected with late blight, with a minimum area of 1 x 1 m were selected at 10 different locations for each category and for each category of infestation 10 spectral observations were made. However for this study, only upto 25 per cent disease infestation was considered, as beyond this there can not be disease reclamation measures.

Other observations related to variety, nutrient and water stress were collected from experimental fields in the Central Potato Research Station in Jalandhar (31.16^{0}N latitude and 75.32^{0}E longitude), Punjab state of India.

The experiment contained potato as the crop (cv. K. Chandramukhi) under study with seven nitrogen treatments in potato viz; 0 kg, 50 kg, 100 kg, 150 kg, 200 kg, 250 kg and 300 kg per hectare. There were four replications for each treatment. The recommended dose of N for potato in CPRS is 180 kg/ha. All the N treatments received a common dose of phosphate (80 kg/ha) and potash (150 kg/ha). Field observations for spectral reflectance were taken on 30th October, when the crop was 25 days old.

The irrigation experiment contained potato as the crop (variety – *Kufri Jyoti*) under study with three levels of irrigation treatments. Potato was planted in the second week of October and the observations were collected on 15th December. By the time of observation the I1 treatment had 2 irrigations, I2 4 and I3 5 irrigations.

To study the difference between varieties four varieties of potato viz; Kufri Chandramukhi, Kufri Jyoti, Kufri Ashoka and Kufri Jawahar were grown. The characteristics of these varieties are given in table 1. The varieties were grown using standard management practices recommended for potato crop. Potato was planted in the second week of October and the observations were collected on 15th December.

Table 1. Salient features of potato varieties grown in the experiment

Variety	**Year of Release**	**Duration (Days)**	**Plant Characteristics**	**Foliage Characteristics**
Kufri Ashoka	1996	70-80 (Early)	Medium tall, erect, medium compact and vigorous	Green, Leaves intermediate, rachis green
Kufri Chandramukhi	1968	80-90 (Early)	Medium tall, spreading, open and vigorous	Grey-green, Leaves open, rachis green
Kufri Jyoti	1968	90-100 (Medium)	Tall, erect, compact and vigorous	Grey-green, Leaves Intermediate, rachis green
Kufri Jawahar	1996	80-90 (Early)	Short, erect, compact and vigorous	Light Green, leaves open, rachis green

2.2 Data Analysis

2.2.1 Method for selection of optimum wavebands

The optimum bands are set of those bands, which have least correlation among themselves, high information content and are able to discriminate the target. These three properties can be quantified through Band-band R^2, Principal component analysis and discriminant analysis, respectively (Thenkabail, 2004).

Band-band r^2 models (BBR^{2}M)

Every single waveband (λi) was correlated with every other waveband (λj) leading to lambda by lambda plots where r^2 was plotted with grey shading i.e. darker to bright scaling for low to high r^2. This helped to determine areas rich in information areas of ("bulls eye") and areas of data redundancy areas of ("empty spots"). A very high correlation (high R^2 value) between any 2 wavebands indicates similar or redundant information. The areas of lowest correlation between wavebands indicate that the two bands contain unique information about the species (Thenkabail et al., 2004). The wavelength combinations of 5 lowest values of r^2 from all the combinations were used for the study. For computation of BBR^2, all wavelength combinations were correlated to each other and than squared the r.

Principal component analysis (PCA)

PCA was used to reduce the 68 wavebands hyperspectral data to a few bands that explain most of the variability. The PCA was carried out using the statistical software SPSS-10. Only the

PCs having eigen values greater than 1 were selected for final analysis.

Stepwise discriminant analysis

The discriminant analysis was carried out for four potato varieties, seven nitrogen levels, three irrigation levels in potato and late blight disease infestation upto 25 percent. The whole range of wavebands were divided into five parts (400-490, 500-590, 600-690, 700-790 and >800 nm) for getting the discriminating wavebands in all the region of the spectrum.

2.2.3 Narrowband Indices

Large number of narrowband vegetation indices was computed for each set of spectral data. The vegetation indices computed for this purpose included, structural indices: SR (Simple ratio), NDVI (Normalized difference vegetation index), RDVI (Renormalized difference vegetation index), MSR (Modified simple ratio), SAVI (Soil adjusted vegetation index), MSAVI (Modified soil adjusted vegetation index), OSAVI (Optimised soil adjusted vegetation index); Chlorophyll indices: MCARI (Modified chlorophyll absorption reflectance index), MCARI1, MCARI2, TCARI (Transformed chlorophyll absorption reflectance index), TVI (Triangular vegetation index), SIPI (Structural insensitive pigment index), NPCI (Normalized pigment chlorophyll index); and Red edge indices: Red edge 750/700, Red edge 740/720 and ZTM (Zarco Tejada and Miller). The details of these indices are presented in table 2. The discriminant analysis was done to find out the best indices, which can differentiate potato varieties, nitrogen levels, irrigation levels and disease infestation. The principal component analysis was performed over the set of vegetation indices, found through discriminant analysis for nitrogen levels. The first two principal components containing about 90% of the variability of the vegetation indices were used for plotting scatter plot of the nitrogen levels.

Table 2. 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).
MSR (Modified SR)	$MSR = ((R_{800} - R_{670})-1) / ((R_{800} + R_{670})^{0.5} + 1)$	Chen (1996)
RDVI (Renormalized Difference Vegetation Index)	$RDVI = (R_{800} - R_{670}) / (R_{800} + R_{670})^{0.5}$	Roujean and Breon (1995)
Chlorophyll/Pigment related indices		
MCARI (Modified CARI)	$MCARI = [(R_{700} - R_{670})-0.2(R_{700} - R_{550})](R_{700}/R_{670})$	Daughtry et al. (2000)
TCARI (Transformed CARI)	$TCARI = 3[(R_{700} - R_{670})-0.2(R_{700} - R_{550})(R_{700}/R_{670})]$	Haboudane et al. (2002)
TVI (Triangular vegetation index)	$TVI = 0.5[120(R_{750} - R_{550}) - 200(R_{670} - R_{550})]$	Broge and Leblanc (2000)
SIPI (Structural insensitive pigment index)	$SIPI = (R_{800} - R_{445})/(R_{800} + R_{680})$	Penuelas et al. (1995)
NPCI (Normalized Pigment Chlorophyll Index)	$NPCI = (R_{680} - R_{430}) / (R_{680} + R_{430})$	Penuelas et al. (1995)
MCARI1	$MCARI1 = 1.2[2.5(R_{800} - R_{670}) - 1.3(R_{800} - R_{550})]$	Haboudane et al. (2004)
MCARI2	$MCARI2 = 1.5[2.5(R_{800} - R_{670}) - 1.3(R_{800} - R_{550})]/[(2R_{800} + 1)^2 - (6R_{800} - 5(R670)^{0.5}) - 0.5]$	Haboudane et al. (2004)
Red edge indices		
Red edge 750~700	$R_{750} - R_{700}$	Gitelson & Merzylak (1997)
Red edge 740~720	$R_{740} - R_{720}$	Vogelmann et al. (1993)
ZTM (Zarco Tejada and Miller)	$ZTM = (R_{750} / R_{710})$	Zarco Tejada et al. (2001)

3. RESULTS AND DISCUSSION

The hyperspectral data in the 400-1070 nm was obtained for four varieties of potato viz; Kufri Chandramukhi, Kufri Jyoti, Kufri Ashoka and Kufri Jawahar, seven nitrogen levels at 0, 50, 100, 150, 200, 250 and 300 kg/ha, three irrigation scheduling in potato and late blight disease infestation in potato crop for early late blight disease detection from disease free to 25 percent infestation.

3.1 Band-band r^2 models (BBR^{2}M) of hyperspectral data

For every vegetation and crop species a rigorous search criterion was developed wherein every single waveband was correlated with every other waveband. A very high correlation (high R^2 value) between any two wavebands indicates similar or redundant information. The areas of lowest correlation between wavebands indicate that the two bands contain unique information about the species (Thenkabail et al. 2004). In order to search for waveband performance, pooled data of four potato crop varieties, seven nitrogen levels, three irrigation levels in potato and four levels of late blight disease infestation were put together and analyzed. The most frequently occurring wavebands in the least correlation set, included the wavelength pertaining to green (520 and 560 nm), red (660-690 nm), red edge (730-740 nm) and NIR (760-810, 960 and 1030 nm) regions of the spectrum.

3.2 Principal component analysis

Principal component analysis (PCA) was carried out to reduce the 69 wavebands into few wavebands. The first three principal components for four potato varieties and late blight disease infestation explained 94.42 and 97.99 % variability whereas first two principal components for seven nitrogen treatments and three irrigation levels 96.64 and 97.77% variability, respectively. Therefore, in order to explain about 95 percent variability, the sixty-nine wavebands can be reduced to two to three new principal component (PC) wavebands (PC1 to PC3). This will lead to reducing the volume of data by about 95 percent. In Table 4, the wavebands that provide the highest factor loadings are listed. Thenkabail et al. (2004) considered the first five wavebands that provide the highest factor loadings for crops, shrubs, grasses, and weeds on first five PCs, which explained the variability of 90 to 97 percent of the dataset. The PC1 was mostly dominated by the NIR region of the spectrum for the vegetation due to very high reflectance in this region however the PC2 and PC3 were mostly dominated by green region (520-580 nm) for irrigation, blue (400-420 nm) and red region for disease (610-690 nm) and red region (620-690 nm) for nitrogen levels and whole visible region for varieties (400-430, 490-510, 630 and 690 nm). Thenkabail et al. (2004) also found that red region dominated in PC2 for crops and weeds.

3.3 Stepwise discriminant analysis

The discriminatory power of hyperspectral data was assessed for four potato varieties, seven nitrogen levels, three levels of irrigation and late blight disease intensity upto 25 percent. The optimal Wilk's lambda values were achieved with fifteen wavebands for differentiating the four varieties of potato, seven wavebands for discriminating seven nitrogen treatments, five wavebands for differentiating the three irrigation levels in potato and late blight disease infestation in potato. The most frequently occurring wavebands for achieving the optimal Wilk's lambda values for four potato varieties, seven nitrogen treatments, three irrigation levels and late blight disease infestation were 700, 730, 750, 760, 780 and 1070 nm, centered at red edge and NIR region of the spectrum.

3.4 Optimal waveband selection

The wavebands that provide the best results in the three methods (Principal component analysis, BBR^{2}M and stepwise discriminant analysis) were pooled together to determine their frequency of occurrence in the 400 to 1070 nm range. The three methods (PCA, BBR^{2}M and SDA) provide complimentary and supplementary information. The PCA explains variability in data and reduces data redundancy, BBR^{2}M eliminates all redundant bands and provides wavebands that best model vegetation characteristics, and the SDA tests the strength of data in separating or discriminating species types.

The most frequently occurring wavelength for potato varieties were 400, 420, 430, 680, 690, 760, 800, 810 and 960 nm. These wavelengths cover the blue, red and NIR region of the spectrum. Patel *et al*. (2003) reported that 560, 670, 710, 870, 1100, 1480, 1700 and 1800 nm bands were highly correlated with fractional cover. The frequency of occurrence 2 or greater than 2 was considered for selection of bands for Nitrogen levels. The wavelengths were 560, 650, 730 and 760 nm. Blackmer et al. (1994) reported that reflectance near 550 and 710 nm were better for detecting corn plant N deficiencies compared with reflectance at other wavelengths. In general, N deficiency usually decreases leaf chlorophyll concentration resulting in an increase in leaf reflectance in both green centered (550 nm) and red edge (700–720 nm) ranges (Daughtry et al., 2000; Zhao et al., 2003).

The wavelengths of 690, 730, 780 and 800 nm were having occurrence of 2 or above considered for selection of late blight disease in potato. Similarly, the frequency of occurrence 2 or greater than 2 was considered for selection of bands for different irrigation scheduling in potato. The wavelengths were 520, 560, 660 and 790 nm.

The wavelengths considered for potato varieties, nitrogen levels, irrigation levels and disease infestation in potato were pooled together to determine their frequency of occurrence in the 400 to 1070 nm range (Figure 1). The highest frequency of occurrence was found in 690 nm (10 times) followed by 560 nm (8 times), 730 and 760 nm (6 times), 780 nm (5 times), 520, 660, 790 and 800 nm (4 times). The wavebands found in all the three analysis covered the green (520 and 560 nm), red (660 and 690 nm), red edge (730 nm) and NIR (760, 790 and 800 nm) region of the spectrum. The wavebands found suitable in our study were shown to have utility as shown by various researchers (Table 3).

Table 3. Selected wavebands for crop stress detection and their significance

Spectral region	Wavelength (nm)	Significance
Green	520, 560	Green band peak or the point maximal reflectance in the visible spectrum. (Thenkabail et al. 2000)
Red	660, 690	Absorption maxima. Maximum Chlorophyll Absorption Greatest soil crop contrast, Sensitive to biomass and LAI (670-680) (Thenkabail et al. 2004). 680 nm is responsible for chlorophyll a pigment estimation (Blackburn, 1998a)
Red edge	730	Plant stress is best detected at red-edge bands centered around 705 nm and 735 nm (Elvidge and Chen, 1995, Thenkabail et al. 1999)
NIR	760,780, 790, 800	Early NIR. More sensitive to changes in chlorophyll content than a broad NIR band. (Thenkabail et al. 2000)

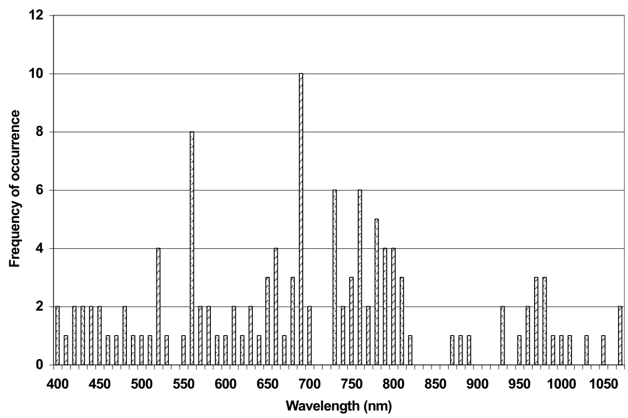

Figure 1. Frequency of occurrence of bands for pooled analysis of potato varieties, nitrogen levels, Irrigation levels in potato and late blight disease infestation in potato

3.5 Selection of best vegetation indices

Apart from the best bands we also tried to select the best indices for crops stress discrimination in potato. Stepwise discriminant analysis was carried out to select the best indices, from the set of indices defined in table 2, for discrimination.

The discriminant analysis of different vegetation indices for four potato varieties showed that simple ratio, ZTM, RE 750/700 and RE 740/720 were able to discriminate four varieties. Nitrogen levels could be discriminated by RE 740/720 and SIPI. Nitrogen concentration in green vegetation is related to chlorophyll content, and therefore indirectly to one of the basic plant physiological processes: photosynthesis (Haboudane et al. 2002). As the nitrogen level increases the SIPI gradually increases upto 200 kg N per hectare due to its effect on chlorophyll concentration. Penuelas et al. (1995) found that SIPI, using these wavelengths, provided that the best estimate of the ratio of Cars:Chl *a* for a range of individual leaves of different conditions. Red edge indices which covered 700 to 750 nm wavelength were found the most significant for differentiating different nitrogen levels. As nitrogen content is directly related to the chlorophyll content of the plant and chlorophyll red edge exhibits the greatest change in reflectance per change in wavelength of any green leaf spectral feature in the visible and NIR (Elvidge and Chen, 1994). The previous studies also indicated that high spectral resolution measurements of the chlorophyll in red edge region (700-795 nm) could be used to detect trace quantities of green vegetation (Elvidge et al. 1993). The disease infestation in potato crop could be differentiated by ZTM, SIPI, RE 750/700 and RE 740/720. Among all the vegetation indices that were found useful for discriminating the nitrogen and disease was related to the red edge position of the spectrum and the ratio of red edge RE 740/720 was found the most suitable. Irrigation levels could be discriminated by simple ratio and TVI. The canopy density and chlorophyll content in plants is dependent on water availability to the plants. Haboudane et al. (2004) reported that Triangular Vegetation Index (TVI) seemed to be a good candidate for green LAI estimations, but its sensitivity to chlorophyll content increases with the increase of canopy density.

4. Conclusion

The present need of agriculture is to increase the production by optimum utilization of resources. Hyperspectral remote sensing could be a valid option for detection of varietal performance, water and nutrient (nitrogen) requirement of the crop as well as the early detection of the disease like late blight in potato. The present study identified the nine bands (520, 560, 660, 690, 730, 760, 780, 790 and 800 nm) which best characterize the potato varieties, nitrogen levels, irrigation levels and early late blight disease detection in potato. The red edge indices performed best for separating variety, disease intensity, and nitrogen application rate. However, other indices like TVI and SR performed well for discrimination between different irrigation treatments.

Acknowledgement

This works was carried out as part of the "Precision Farming" project under Earth Observations Applications Mission of Department of Space. Authors are grateful to Dr. R. R. Navalgund, Director, SAC and Dr. J. S. Parihar, Deputy Director, RESA/SAC for encouragement. Authors are also grateful to Dr. S. K. Pandey, Director, Central Potato Research Institute, Shimla for facilitating the required fieldwork at Central Potato Research Station, Jalandhar. Thanks are due to Dr. Namrata Jain for the help during field observations.

References

Anonymous (1947) The measurement of potato blight. *Trans British Mycological Soc.* 31: 140-141

Apan, A., Held, A., Phinn, S. and Markley, J., 2004, Detecting sugarcane 'orange rust' disease using EO-1 Hyperion hyperspectral imagery. *Int. J. Remote Sens.* 25, pp. 489–498.

Birth, G.S. and McVey, G. (1968). Measuring the colour of growing turf with a reflectance spectrophotometer. *Agron. J.* 60 : 640.

Blackburn, G. A. (1998a). Spectral indices for estimating photosynthetic pigment concentrations: a test using senescent tree leaves, *Int. J. Remote Sens.*, 19 (4): 657-675.

Blackmer, T.M., Schepers, J.S. and Varvel, G.E. 1994). Light reflectance compared with other nitrogen stress measurements in corn leaves. *Agron. J.,* 86: 934–938.

Broge, N. H. and Leblanc, E. (2000). Comparing predictive power and stability of broad-band and hyperspectral vegetation indices fro estimation of green leaf area index and canopy chlorophyll density. *Remote Sens. Environ.* 76 : 156-172.

Carter, G.A. (1994). Ratios of leaf reflectances in narrow wavebands as indicators of plant stress. *Int. J. Remote Sens.*, 15: 697-703.

Chen, J.M. (1996). Evaluation of vegetation indices and a modified simple ratio for boreal applications. *Can. J. Remote. Sens.*, Vol. 22 : 229-242.

Collins, W. (1978) Remote sensing of crop type and maturity. *Photogramm. Engg Remote Sens.* 44: 43-55.

Daughtry, C.H.T., Walthall, C.L., Kim, M.S., de Colstoun, E.B. and Mc- Murtrey III, J.E., (2000). Estimating corn leaf chlorophyll concentration from leaf and canopy reflectance. *Remote Sens. Environ.* 74: 229–239.

Elvidge, C. D., Chen, Z., and Groeneveld, D. P. (1993), Detection of trace quantities of green vegetation in 1990 AVIRIS data, *Remote Sens. Environ.* 44:271-279.

Elvidge, C.D. and Chen, Z., 1995. Comparison of broadband and narrow-band red and near-infrared vegetation indices, *Remote Sens. Environ.* 54 : 38-48.

FieldSpec®Pro (2000). User's Guide Manual Release, Analytical Spectral Devices Inc., Boulder, CO, USA.

Filella, I., Serrano, L., Serra, J., & Pen˜ uelas, J. (1995). Evaluating wheat nitrogen status with canopy reflectance indices and discriminant analysis. *Crop Sci.,* 35, 1400– 1405.

Gitelson A.A. & Merzylak, M. N. (1996) Signature analysis of leaf reflectance spectra: Algorithm development for remote sensing. *J. Plant Physiol*. 148:493-500.

Haboudane, D., Miller, J.R, Pattey, E., Zarco-Tejada, P. J. & Strachan, I. B. (2004). Hyperspectral vegetation indices and novel algorithms for predicting green LAI of crop canopies: Modeling and validation in the context of precision agriculture. *Remote Sens. Environ.*, 90:337-352.

Haboudane, D., Miller, J.R, Trembley, N., Zarco-Tejada, P. J. & Dextraze, L. (2002). Integrated Narrow band vegetation indices for prediction of crop chlorophyll content for application to precision agriculture. *Remote Sens. Environ.*, 81:416-426.

Hatfield P L, Pinter P J Jr (1993) Remote sensing for crop protection. Crop Protection 12: 403-413

Huete, A.R. (1988). A soil adjusted vegetation index (SAVI). *Remote Sens. Environ.,* 17, 37-53.

Jain, Namrata, Ray, S. S., Singh, J. P. and Panigrahy, S. (2007) Use of hyperspectral data to assess the effects of different nitrogen applications on a potato crop. *Precision Agric.* 8(4-5): 225-239.

Janetos, A.C. and Justice, C.O. (2000). Land cover and global productivity: A measurement strategy for the NASA programme. *Int. J. Remote Sens.*, 216) : 1491-1512.

Knipling E. B. (1970) Physical and physiological basis for the reflectance of visible and near-infrared radiation from vegetation. *Remote Sens. Environ.* 1(3): 155-159.

Lyon, J.G., Yuan, D., Lunetta, R.S. and Elvidge, C.D. (1998). A change detection experiment using vegetation indices, *Photogramm. Engg. Remote Sens.*, 64: 143-150.

Mariotti, M., Ercoli, L. and Masoni, A., (1996). Spectral properties of iron-deficient corn and sunflower leaves, *Remote Sens. Environ.* 58: 282-288.

McGwire, K., Minor, T. and Fenstermaker, L. (2000). Hyperspectral Mixture Modeling for Quantifying Sparse Vegetation Cover in Arid Environments, *Remote Sens. Environ.,* 723): 360-374.

Patel, N.K., Saxena, R.K. and Shiwalkar, A. (2003). High spectral resolution data as indicator of soil parameters and ground cover. *ISRS Symp.*, Thiruvananthpuram, Dec. 9-12.

Penuelas, J., Gamon, J.A., Fredeen, J. Merino and Field, C.B. (1994). Reflectance indices associated with physiological changes in nitrogen and water limited sunflower leaves. *Remote Sens. Environ.* 48 : 135-146.

Penuelas, J., Filella, I., Lloret, P., Munoz, F. and Vilajeliu, M. (1995). Reflectance assessment of mite effects on apple trees, *Int. J. Remote Sens.* 16: 2727-2733.

Pozdnyakova L , Oudemans P V, Hughes M G and Giménez D (2002) Estimation of spatial and spectral properties of phytophthora root rot and its effects on cranberry yield. *Computers Electronics Agrl*. 37: 57-70

Qi, J., Chehbouni, A., Huete, A. R., Kerr, Y. H., & Soroshian, S. (1994). A modified soil vegetation index. *Remote Sens. Environ.* 48:119-126

Qin, Z, Zhang M (2005) Detection of rice sheath blight for in-season disease management using multispectral remote sensing. *Int. J. Appl. Earth Observ. Geoinformation.* 7: 115–128

Ray, S. S., Das, Gargi, Singh, J. P. and Panigrahy, Sushma (2006) Evaluation of Hyperspectral Indices for LAI Estimation and Discrimination of Potato Crop under Different Irrigation Treatments. *Int. J. Remote Sens.* 27(24): 5373-5387.

Rondeaux, G., Steven, M. and Barret, F. (1996) Optimization of soil adjusted vegetation indices. *Remote Sens. Environ.* 55, 95-107.

Roujean, J.L. and Breon, E.M. (1995). Estimation PAR absorbed by vegetation from bi-directional reflectance measurements. *Remote Sens. Environ.* Vol 51 : 375-384.

Rouse, J.W., Haas, R.H., Schell, J.A. and Deering, D.W. (1973). Monitoring vegetation system in great plains with ERTS. Proc. 3rd ERTS-1 Symp., GSFC, NASA, SP-351. pp. 48-62.

Strachan, I.B., Pattey, E. and Boisvert, J.B. (2002). Impact of nitrogen and environmental conditions on corn as detected by hyperspectral reflectance. *Remote Sens. Environ*. 80: 213-214.

Thenkabail P.S., Smith, R.B., and De Pauw, E. (1999). Hyperspectral vegetation indices for determining agricultural crop characteristics. CEO research publication series 1. ISBN: 0-9671303-0-1, Center for Earth Observation, Yale University, USA. 40

Thenkabail, P. S. (2002) Optimal Hyperspectral Narrowbands for Discriminating Agricultural crops. *Remote Sens. Rev*. 20:257-291.

Thenkabail, P.S., Enclona, E.A., Ashton, M.S. and Meer, B. Van Der. (2004). Accuracy assessments of hyperspectral waveband performance for vegetation analysis applications. *Remote Sens. Environ.* 91: 354-376.

Vogelman, J. E., Rock, B. N. and Moss, D. M. (1993). Red edge spectral measurements from sugra maple leaves. *Int. J. Remote Sens.* 14(8): 1563-1575.

Zarco-Tejada, P. J., Miller, J.R, Nolland, T. L., Mohammed, G. H., Sampson, P.H. (2001) Scaling up and model inversion methods with narrow-band optical indices for chlorophyll content estimation in closed forest canopies with hyperspectral data. *IEEE Trans. Geosci. Remote Sens.* 39(7):1491-1507.

Zhang, M., Qin, Z., Liu, X. and Ustin, S.L., (2003). Detection of stress in tomatoes induced by late blight disease in California, USA, using hyperspectral remote sensing. *Int. J. Appl. Earth Observ. Geoinformatics*, 4: 295–310.

Zhao, D., Reddy, K.R., Kakani, V.G., Read, J.J. and Carter, G.A., (2003). Corn (Zea mays L.) growth, leaf pigment concentration, photosynthesis and leaf hyperspectral reflectance properties as affected by nitrogen supply. *Plant Soil*, 257: 205–217.

Zhihao, Qin and Minghua, Zhang (2005). Detection of rice sheath blight for in-season disease management using multispectral remote sensing *Int. J. Appl. Earth Observ. Geoinformatics,* 7(2): 115-128.