VERSITA

INTERNATIONAL
Agrophysics
www.international-agrophysics.org

Int. Agrophys., 2012, 26,103-108
doi: 10.2478/v10247-012-0016-8

Soil-line vegetation indices for corn nitrogen content prediction

N. Bagheri[1]*, *H. Ahmadi*[1], *S.K. Alavipanah*[2], *and M. Omid*[1]

[1]Department of Agricultural Technology and Engineering, [2]Department of Geography,
University of Tehran, Karaj, Iran

Received February 6, 2011; accepted March 11, 2011

A b s t r a c t. The soil-line vegetation indices for prediction of corn canopy nitrogen content were investigated. Results indicated that the vegetation indices applied were correlated with corn canopy nitrogen content and the wavelengths between 630-860 nm are suitable for nitrogen diagnosis. The second-order polynomial equation was the best model for nitrogen content prediction among different regression types. Analyses based on both predicted and measured data were carried out to compare the performance of existing vegetation indices.

K e y w o r d s: soil-line vegetation indices, satellite remote sensing, corn, nitrogen

INTRODUCTION

Remote sensing offers the possibility of monitoring agricultural areas for rapid and continuous assessment of plant, soil and water resources (Kostrzewski *et al*., 2002). Beside the large areas that can be studied, the increased application of remote sensing systems in agricultural management is mainly due to the improvements in spatial, spectral and temporal resolution of remotely sensed observations (Karimi *et al*., 2005). Researches show that determination of spectral plant status by utilising visible and near-infrared spectral responses from plant canopies is possible (Min and Lee, 2005).

One of the applications of remote sensing is determination of plant physiological properties. Different studies have been carried out to model crop properties with different vegetation indices. For example, potato canopy nitrogen content with red edge position (derived from reflectance measurements) (Jongschaap and Booij, 2004), predicting leaf area index (LAI) using SAVI (soil-adjusted vegetation index), MSAVI2 (modified soil-adjusted vegetation index) and SARVI (soil and atmospherically resistant vegetation index) (Haboudane *et al*., 2004), NDVI (normalized difference vegetation index) and GNDVI (green normalized difference vegetation index) (Eldaw Elwadie *et al*., 2005), predicting grain protein content (Zhao *et al*., 2005), estimating sugar beet residue nitrogen credit (Beeri *et al*., 2005), predicting rice nitrogen content with RVI (ratio vegetation index) and NDVI (Jin-Heng *et al*., 2006), nitrogen doses discrimination of wheat (Sena Junior *et al*., 2007), apple tree nitrogen treatment with NDVI (Perry and Davenport, 2007), wheat nitrogen content (Feng *et al*., 2008), determining rice nitrogen topdressing rate based on real-time canopy reflectance spectra (Xue and Yang, 2008), estimating nitrogen uptake of barely with NDVI, GNDVI, RGNDI (red and green normalized difference vegetation index), RGVI (red and green ratio vegetation index), RVI, GVI (green vegetation index) (Li *et al*., 2008; and Pagola *et al*., 2009).

Many researchers assessed the correlation between different vegetation indices and the physiological status of crops. They were mostly concerned with finding out suitable wavelengths for plant properties by spectro-radiometer and mostly with laboratory experiments. As those results are not universalized for real conditions, this research was conducted to evaluate satellite remote sensing for nitrogen content diagnosis on farm. Also, as the soil-line vegetation indices are sensitive to vegetation and minimize soil effects, they could be useful for physiological properties of vegetation such as nitrogen content. Hence, the objectives of this study were to:

– investigate the possibility of using the soil-line vegetation indices to determine nitrogen content in corn canopy on filed,
– develop models to predict corn nitrogen content with soil-line vegetation indices,

*Corresponding author's e-mail: nikroozbagheri@yahoo.com.au

– evaluate ASTER (the advanced space borne thermal emission and reflection radiometer) satellite imagery for the prediction of nitrogen content in corn canopy.

MATERIALS AND METHODS

Field experiments were carried out on a 23 ha single cross corn farm in Pakdasht, Iran (35°30'N, 51°36'E), on September 4, 2009. The field was fertilized according to usual practice and nitrogen was applied as urea solution five times, *via* 5 stage irrigations (Table 1). False colour composite (FCC) imagery of the studied area is shown in Fig. 1.

Before sampling, the farm was meshed and coordination was collected by Magellan Explorist-600 GPS with the accuracy of three meters and the farm map was reconstructed with AutoCAD software. For each pixel, five samples (with an area of 1 m^2 for each sample) were harvested and average data were used for analysis of total nitrogen content. Leaves were separated and, after drying in an oven at 70°C for 48 h and weighting on digital scale (with accuracy of 0.1 g), the samples were ground to pass 1mm screen, then stored in plastic bags and sent to the laboratory for determination of total nitrogen content in leaf tissues by the Kjeldahl method (Xue and Yang, 2008). Figure 2 shows the farm meshing and plant samples.

T a b l e 1. Agronomical calendar in experimental farm in 2009

No.	Farm activities	Date
1	Tillage	June 12
2	Cultivating	June 15
3	Seeding	July 5
4	1st irrigation and N-application	August 9
5	2nd irrigation and N-application	August 26
6	3rd irrigation and N-application	August 30
7	4th irrigation and N-application	September 9
8	5th irrigation and N-application	September 20
9	Harvest	October 10

Parameters which are important for vegetation studies with satellite remote sensing are ground resolution, number of bands and wavelengths ranges. In comparison with different sensors, the ASTER imagery has a wide range of wavelengths and good resolution. Hence, in this research, imagery of the study area was acquired with the ASTER for a sunny and cloudless day on September 4, 2009. This sensor has 3 spectral bands in the visible and near-infrared (VNIR) in 520-860 nm, 6 bands in the short-wave-infrared (SWIR) in 1 600-2 430 nm and 5 bands in the thermal infrared (TIR) region in 8 125-1 1650 nm with 15, 30 and 90 m ground resolution, respectively (Abrams, 2003).

Image processing was carried out with ENVI remote sensing software. We used only imagery acquired at a single point in time. Since a low atmospheric water content and clear sky were present at the time of image acquisition, no atmospheric correction was performed. Geometric correction was performed with 1:25 000 scale file maps. A total of 24 sample points were selected with good scattering in the whole image. The nearest neighbour method was used for resampling of data. RMS of geometric correction was 0.2 pixels.

Application of remote sensing techniques in agriculture can be successful only if it is based on the knowledge of the spectral-temporal properties of different crops and bare soils (Piekarczyk, 2001). Over the past few years, expanding research activities have focused on understanding the relationships between vegetation optical properties and photosynthetic pigments contents within green leaf tissues.

Soil reflectance in red and that in near infrared are highly correlated with a positive correlation coefficient which makes an assumption line which is called soil line. Soil line in an area with a mixture of bare soil and varied coverage of vegetation constitutes a triangle shape where the soil line is the base of the triangle. As soil-line vegetation indices are sensitive to crop reflectance and its properties and they can minimize soil brightness, they were used to predict corn canopy nitrogen content.

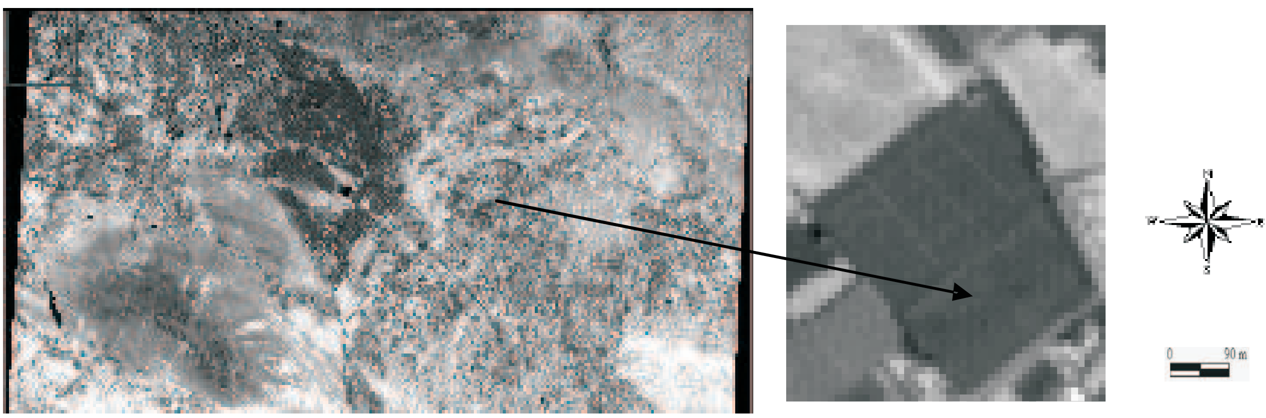

Fig. 1. FCC (3-2-1 composition) imagery of ASTER sensor of the studied area.

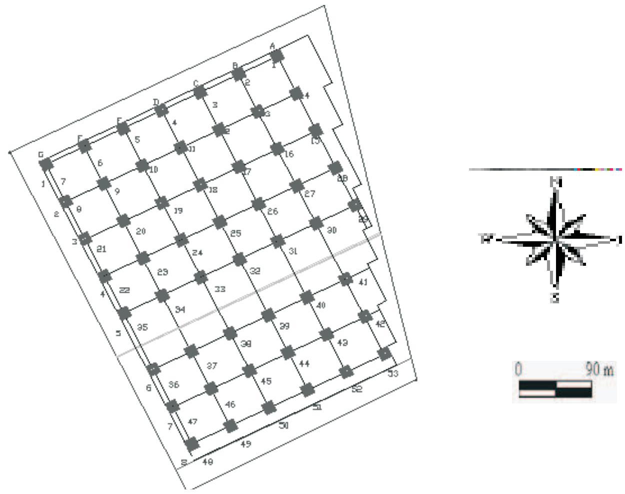

Fig. 2. Farm meshing and plant sampling.

SAVI, OSAVI (optimized soil-adjusted vegetation index) and MSAVI2 were developed to minimize the soil background influence and brightness. SAVI includes a canopy background adjustment factor L. The factor L is a function of vegetation density, and its determination requires a prior knowledge of vegetation amounts. The value of factor L is critical in the minimisation of soil optical properties effects on vegetation reflectance. Huete (1988) determined that an adjustment factor of 0.5 could be used across different vegetation densities and different soil types (Huete, 1988).

Attempting to improve SAVI with regard to the differences in soil background developed an improved SAVI (MSAVI2) with a self-adjustment factor L that does not appear in the formulation of MSAVI2 (Qi *et al*., 1994). It is specifically designed for areas with low vegetation to minimize the effect of bare soil. In all the formulas, NIR and R are near infrared and red bands, respectively (Haboudane *et al*., 2004, Lawrence and Ripple, 1998):

$$\text{SAVI} = \frac{(1+\text{L})(\text{NIR}-\text{R})}{(\text{NIR}+\text{R}+\text{L})}\ \text{L}=0.5, \qquad (1)$$

$$\text{MSAVI2} = 0.5\left[2\text{NIR}+1-\sqrt{(2\text{NIR}+1)^2-8(\text{NIR}-\text{R})}\right], \qquad (2)$$

$$\text{OSAVI} = 1.6\frac{\text{NIR}-\text{R}}{\text{NIR}+\text{R}+0.16}. \qquad (3)$$

RESULTS AND DISCUSSION

To classify two bands of image data, 2D scatter plots were used. Figure 3 shows the specification of the NIR, red and green bands of ASTER imagery to each other.

In Fig. 3 corn canopy reflectance in the NIR region is higher than that of the Red and Green bands. Corn canopy reflectance decreased in the visible region and increased in the NIR region. This trend was expected, as the corn pigment content increases with growth and adequate nitrogen availability, resulting in more visible and NIR light absorption. With plant growth and sufficient nitrogen availability, the increased amount of biomass causes higher reflectance in the NIR region. Pixels with higher NIR reflectance and lower red reflectance are dense vegetation cover, the base of the 'triangle' shape is the soil line.

To determine the best model for the prediction of nitrogen content, different regression types were investigated. Table 2 shows the specification of linear, logarithmic, second-order, power and exponential regression types for vegetation indices. The Table shows that the second-order polynomial equation has the highest correlation with nitrogen content. Figures 4-6 show the relationships between corn canopy nitrogen content and soil-line vegetation indices with second-order polynomial equations.

The results of Figs 4-6 show that all vegetation indices change with changing nitrogen content and the vegetation indices were significantly sensitive and correlated to corn canopy nitrogen content. It is concluded that SAVI, OSAVI and MSAVI2 exhibit a similar trend to nitrogen variability and all of them have high correlation to nitrogen content because of omitting soil optical property effects on vegetation reflectance and minimising the background influence. As it

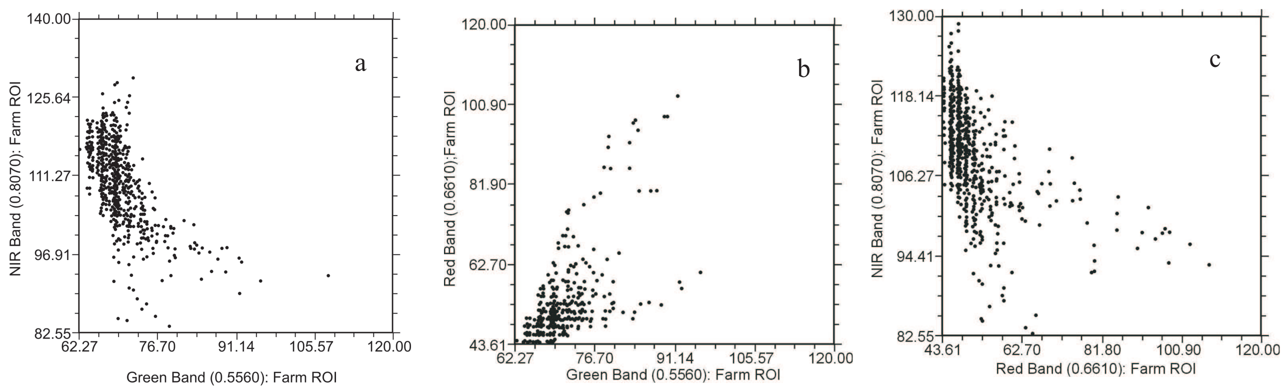

Fig. 3. NIR, red and green scatter plots.

T a b l e 2. Regression types for predicting nitrogen content with SAVI, OSAVI and MSAVI2

Indices	Regression type	Formula	R^2
SAVI	Linear	$N = 4.6541(SAVI) - 0.5592$	0.730
	Logarithmic	$N = 2.7595Ln(SAVI) + 3.6337$	0.721
	Second-order polynomial	$N = 6.3707(SAVI)^2 - 2.8503(SAVI) + 1.6335$	0.737
	Power	$N = 4.2162(SAVI)^{1.2496}$	0.733
	Exponential	$N = 0.6126 exp.(2.143(SAVI))$	0.733
OSAVI	Linear	$N = 7.5653(OSAVI) - 1.3339$	0.732
	Logarithmic	$N = 3.4247Ln(OSAVI) + 4.8187$	0.727
	Second-order polynomial	$N = 1.7276(OSAVI)^2 + 5.986(OSAVI) - 0.9756$	0.733
	Power	$N = 7.8182(OSAVI)^{1.6752}$	0.706
	Exponential	$N = 0.3883 exp (3.6854(OSAVI))$	0.706
MSAVI2	Linear	$N = 6.4544(MSAVI2)-1.4135$	0.721
	Logarithmic	$N = 3.5945 Ln(MSAVI2)+4.2937$	0.710
	Second-order polynomial	$N = 7.349(MSAVI2)^2-1.7864(MSAVI2)+0.8866$	0.747
	Power	$N = 5.6873(MSAVI2)^{1.6438}$	0.718
	Exponential	$N = 0.4197 exp (2.9457(MSAVI2))$	0.727

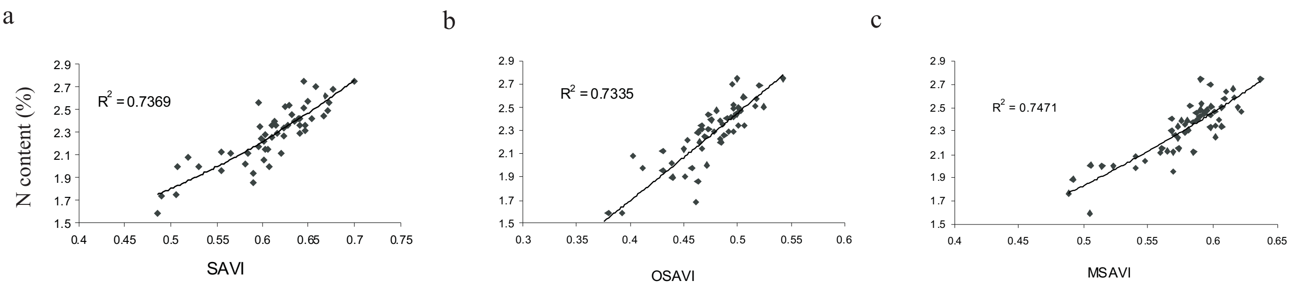

Fig. 4. Relationship between corn nitrogen content and: a – SAVI, b – OSAVI, c – MSAVI2.

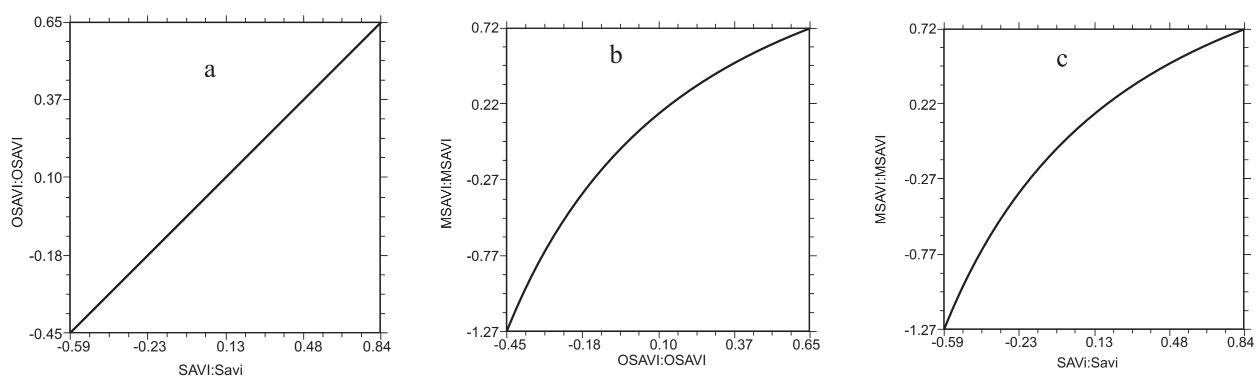

Fig. 5. Vegetation indices scatter plots: a – OSAVI-SAVI, b – MSAVI2-OSAVI, c – MSAVI2-SAVI.

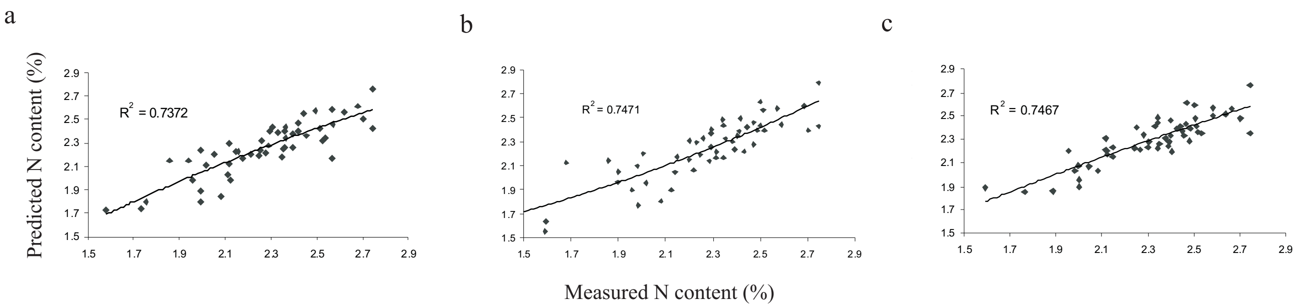

Fig. 6. Relationship between measured and predicted corn nitrogen content with : a – SAVI, b – OSAVI, c – MSAVI2.

T a b l e 3. Regression models for estimation of corn canopy nitrogen content by vegetation indices

Indices	Regression model	R^2
SAVI	N = -0.1337(SAVI)^2+1.3483(SAVI)-0.1077	0.7369
OSAVI	N = 0.1529(OSAVI)^2-0.0889(OSAVI)+1.240	0.7335
MSAVI2	N = -0.055(MSAVI2)^2-0.9439(MSAVI2)+0.408	0.7467

is shown in Table 1, spectral indices are dependent on the NIR and red bands, whereas for ASTER imagery the NIR and red bands are in the 630-690 nm and in 760-860 nm wavelengths, respectively. Hence, it shows that the wavelengths between 630 and 860 nm are suitable for nitrogen diagnosis. Other researches showed similar results, such as: Blackmer *et al*. (1996) found 550-710 nm wavelength; Lough and Varco (2000) found 550 nm; Buscaglia and Varco (2002) found wavelengths between 550 to 728 nm for cotton; Borhan *et al*. (2004) found 550-710 nm for corn and 540-680 and 740-1070 for rice; Min and Lee (2005) found the wavelengths of 480 and 580 nm for citrus; and Reum and Zhang (2007) found the wavelengths 550-700 nm for corn as useful wavelengths for the diagnosis of nitrogen content. The correlation between different vegetation indices is shown in Fig. 5. There is a linear relationship between OSAVI and SAVI. Furthermore, the relationship between MSAVI2-OSAVI and MSAVI2-SAVI is logarithmic. As these vegetation indices are strongly correlated with each other, they show similar trends with nitrogen content variation.

To investigate the accuracy of regression models for the prediction of corn canopy nitrogen content, the measured and predicted nitrogen values were compared. Equations describing these relationships vary in second order polynomial equation which had the highest correlation with nitrogen content between different regression models.

A total of 53 new samples were chosen randomly and harvested to determine nitrogen accumulation and were compared with predicted data by SAVI, OSAVI and MSAVI2. The relationship between predicted and measured nitrogen contents for each vegetation index is shown in Fig. 6. The results of comparison with different regression types for three vegetation indices showed that the second-order polynomial equation is the best regression type to model the correlation between vegetation indices and nitrogen content.

A summary of final regression models for estimation of corn canopy nitrogen contents by soil-line vegetation indices is presented in Table 3. The results showed that all investigated vegetation indices were found to be highly correlated to corn canopy nitrogen contents and can be successfully used to predict and model crop canopy nitrogen content during the vegetation period. The performance of MSAVI2 (with R^2=0.7467) in predicting corn nitrogen content is better than that of SAVI and OSAVI because of its ability to minimize high reflectance of the soil.

CONCLUSIONS

1. The vegetation indices, SAVI, OSAVI and MSAVI2, had high correlation to corn canopy nitrogen content.

2. The wavelengths between 630-860 nm are suitable for nitrogen content diagnosis.

3. Soil-line vegetation indices can be successfully used to predict and model crop canopy nitrogen content during the vegetation period.

4. ASTER imagery as a multi spectral remote sensing system is capable enough to be adapted for predicting corn canopy nitrogen content.

REFERENCES

Abrams M., 2003. The advanced space borne thermal emission and reflection radiometer (ASTER): data products for the high spatial resolution imager on NASA's Terra platform. J. Int. J. Remote Sens., 21, 847-859.

Beeri O., Phillips R., Carson P., and Liebig M., 2005. Alternate satellite models for estimation of sugar beet residue nitrogen credit. J. Agric. Ecosys. Environ., 107, 21-35.

Blackmer T.M., Schepers J.S., Varvel G.E., and Walter-Shea E.A., 1996. Nitrogen deficiency detection using reflected short-wave radiation from irrigated corn canopies. J. Agron., 88, 1-5.

Borhan M., Panigrahi S., Lorenzen S., and Gu H., 2004. Multi-spectral and color imaging techniques for nitrate and chlorophyll determination of potato leaves in a controlled environment. J. Trans. ASABE, 47(2), 599-608.

Buscaglia H.J. and Varco J.J., 2002. Early detection of cotton leaf nitrogen status using leaf reflectance. J. Plant Nutr., 25, 2067-2080.

Eldaw Elwadie M., Francis J., and Qi J., 2005. Remote sensing of canopy dynamics and biophysical variables estimation of corn in Michigan. J. Agron., 97, 99-105.

Feng W., Yao X., Zhu Y., Tian Y.C., and Cao W.X., 2008. Monitoring leaf nitrogen status with hyper spectral reflectance in wheat. J. Eur. Agron., 28, 394-404.

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

Huete A.R., 1988. A soil vegetation adjusted index (SAVI). J. Remote Sens. Environ., 25, 295-309.

Jin-Heng Z., Ke W., Bailey J.S., and Ren-Chao W., 2006. Predicting nitrogen status of rice using multi spectral data at canopy scale. Pedosphere, 16(1), 108-117.

Jongschaap R.E.E. and Booij R., 2004. Spectral measurements at different spatial scales in potato: relating leaf, plant and canopy status. J. Int. Appl. Earth Obser. Geoinf., 5, 205-218.

Karimi Y., Prasher S.O., Mcnairn H., Bonnell R.B., Dutilleul P., and Goel P.K., 2005. Discriminant analysis of hyper spectral data for assessing water and nitrogen stresses in corn. J. Trans. ASABE, 48(2), 805-813.

Kostrzewski M., Waller P., Guertin P., Haberland J., Colaizzi P., Barnes E., Thompson T., Clarke T., Riley E., and Choi C., 2002. Ground-based remote sensing of water and nitrogen stress. J. Trans. ASABE, 46(1), 29-38.

Lawrence R.L. and Ripple W.J., 1998. Comparisons among vegetation indices and bandwise regression in a highly disturbed, heterogeneous landscape. J. Remote Sens. Environ., 64, 91-102.

Li F., Gnyp M., Jia L., Miao Y., Yu Z., Koppe W., Bareth G., Chen X., and Zhang F., 2008. Estimating N status of winter wheat using a handheld spectrometer in the North China plain. J. Field Crops. Res., 106, 77-85.

Lough L.J. and Varco L.L., 2000. Effects of varing N and K nutrition on the spectral reflectance properties of cotton. Proc. 5th Int. Conf. Precision Agric., July 16-19, Bloomington, MI, USA.

Min M. and Lee W.S., 2005. Determination of significant wavelengths and prediction of nitrogen content for citrus. J. Trans. ASABE, 48(2), 455-461.

Pagola M., Ortiz R., Irigoyen I., Bustince H., Barrenechea E., Aparicio-Tejo P., Lamsfus C., and Lasa B., 2008. New method to assess barely nitrogen nutrition status based on image colour analysis comparison with SPAD-502. J. Comput. Electron. Agric., 65(2), 213-218.

Perry M.E. and Davenport J.R., 2007. Spectral and spatial differences in response of vegetation indices to nitrogen treatments on apple. J. Comput. Electron. Agric., 59, 56-65.

Piekarczyk J., 2001. Studies of soil temperature on the basis of satellite data. Int. Agrophysics, 15, 101-107.

Qi J., Chehbouni A., Huete A.R., Keer Y.H., and Sorooshian S., 1994. A modified soil vegetation adjusted index. J. Remote Sens. Environ., 48, 119-126.

Reum D. and Zhang Q., 2007. Wavelet based multi-spectral image analysis of maize leaf chlorophyll content. J. Comput. Electron. Agric., 56, 60-71.

Sena D.G., jr, Pinto F.A.C., Queiroz D.M., and Souza M.A., 2007. Multivariate classifiers using image texture features for nitrogen doses discrimination in wheat. Proc. ASABE Annual Meeting, June 15-17, Minneapolis, MI, USA.

Xue L. and Yang L., 2008. Recommendations for nitrogen fertilizer topdressing rates in rice using canopy reflectance spectra. J. Biosyst. Eng., 100, 524-534.

Zhao C., Liu L., Wang J., Huang W., Song X., and Li C., 2005. Predicting grain protein content of winter wheat using remote sensing data based on nitrogen status and water stress. Int. J. Appl. Earth Obser. Geoinf., 7, 1-9.