EVALUATION OF DIFFERENCES IN CORN BIOMASS AND NITROGEN UPTAKE AT VARIOUS GROWTH STAGES USING SPECTRAL VEGETATION INDICES

M. S. Torino, B.V. Ortiz, J. P. Fulton, K. Balkcom

M. S. Torino, B.V. Ortiz, K. Balkcom

Agronomy and Soils Department
Auburn University
Auburn, Alabama

J. P. Fulton
Biosystems Engineering
Auburn University
Auburn, Alabama

ABSTRACT

Application of canopy sensors for nitrogen (N) fertilizer management for corn grain production in the Southeast US requires first the identification of the relationship between field-measured crop status and sensor-measured canopy spectral reflectance. A nitrogen test was conducted between 2009 and 2011 at three research stations in Alabama to identify the best vegetation index and corn growth stage to assess differences in biomass and nitrogen uptake from corn receiving various N application rates. Nitrogen treatments included five N rates at 0, 56, 112, 168, 224, 280 kg ha-1 applied at planting. At each location, data of SPAD, LAI, leaf N tissue, and canopy spectral reflectance were collected at V6, V8, V10 corn growth stages. A canonical correlation analysis was conducted to identify the vegetation indices best correlating with field-measured crop status variables and the type of relations existing between both groups of variables. Vegetation indices that include red-edge wavelength resulted in an overall higher correlation than others. Since higher correlations were consistent across all growth stages, (V6 to V10) VIs containing red-edge have the potential to be utilized in VRA-N. Results from this study will be utilized in developing an algorithm for variable rate application of nitrogen in the Alabama.

Keywords: Corn, vegetation index, nitrogen, near infrared, red edge, remote sensing, variable rate.

INTRODUCTION

Nitrogen (N) is the main fertilizer in corn production since it has a high impact on production cost and yield (Stone et al., 2010). The use of nitrogen as an inorganic fertilizer has been subject of several studies for economical and environmental implications. Due to it dependency on fossil fuels cost, nitrogen fertilizer price increased by 130 percent from 2000 to 2007 (Huang, 2007).

Concerning of the environmental impacts, an excessive use of nitrogen on agriculture has been raised. Raun and Johnson (1999) reported a 33 percent worldwide nitrogen use efficiency (NUE) in cereal grains showing the need for developing new management tools to reduce nitrogen loose in agriculture and increasing use efficiency. Based on those numbers, 67 percent of the N applied every year is been lost from the system implying a significant water contamination.

Nitrogen fertilizer recommendations are specific to each zone or environment, and mainly depended on soil and weather conditions. For instance, northern states' extension agencies like Iowa State University Extension (ISUE, 1997) include in their nitrogen recommendations the use of soil N analysis, while states agencies in the southeast like Alabama Cooperative Extension Systems (ACES, 2012) do not. Recommendations for N side-dress uniform rate for corn grain production in Alabama are essentially focused on the average yield potential in the area of 135kg N ha-1 (ACES, 2012). This rate is modified by a factor based on N starter, preceding crop and irrigation, but not accounting for initial soil N. In Alabama, due to sandy soils and high rainfall there is not significant inorganic N available for the plant in the soil profile.

Nitrogen use efficiency is highly dependent on weather and soil conditions (Raun and Johnson., 1999). Weather and soil temporal and spatial variability affect NUE from year to year (Hollinger and Hoeft., 1986). Thus, many efforts have been done to improve NUE, including N simulation models (Setiyono et al., 2011) and remote sensing. Remote sensing is used in agriculture to assess crop status based on plant spectral reflectance (Seelan et al., 2003; Sullivan et al., 2005; Miao et al., 2009; Thorp et al., 2008). Because remote sensors are able to assess N deficient plants lacking of greenness and biomass, several studies support the use of this technology for variable rate application of N (VRA-N) (Raun et al., 2002; Mullen et al., 2003; Teal et al., 2006; Solari et al., 2008; Kitchen et al., 2010; Solie et al., 2012). Furthermore, Roberts et al., (2010) reported N savings of 10 to 45 lb acre-1 resulting in profits from 10$ to 20$ acre^{-1} using sensors for corn VRA-N.

Variable rate application of nitrogen assisted by remote sensors requires the use of a vegetation index (VI) accurately assessing plant status (chlorophyll and biomass). A VI is a ratio or combination between different reflectance wavelengths in the electromagnetic spectrum. Normalized difference vegetation index (NDVI) is the normalized difference between near infrared (NIR) and red (Red) wavelength, and it is one of the most widely used VI for green biomass (NOAA, 2009). Spectral reflectance data in the form of VIs can be used to indirectly assess in-season yield potential and a specific N fertilizer rate to achieve the potential yield. Many sensors available in the market like GreenSeeker (Trimble.CO) and CropCircle (Holland Scientific.CO) calculate NDVI which is used in algorithms for VRA-N. However, other indices can also be calculated using data from independent wavelengths.

Variable rate application nitrogen aided by remote sensors is usually conducted after V8 corn growth stage in the Midwest (Teal et al., 2006). Because delaying N application to V8 or later growth stages in Alabama may result on N stress due to sandy soils and high rainfall in the Coastal Plain region of the state, farmers in the Southeast tend to apply N as early as the V6 growth stage. A low correlation between NDVI at V6 corn growth stage and yield was reported in Oklahoma (Teal et al., 2006). Therefore, a VI with higher correlation is needed to assess corn yield potential early in the season. Thus, the aim of this project is to identify a VI that best correlate with field plant measurement to assess biomass and chlorophyll (Chl) content at early corn growth stages for VRA-N.

Materials and methods

A nitrogen study took place at three Auburn University Research Stations in Alabama in 2010 and 2011. The research stations were, Gulf Coast Research and Extension Center (GCS) in Fiarhope (30°32’09.21”N, 87°52’39.15”W, 34m from sea level), E.V. Smith Research Center (EVS) in Shorter (32°25’43.43”N, 85°53’34.81”W, 69m from sea level) and Tennessee Valley Research and Extension Center (TVS) in Belle Mine (34°41’05.37N, 86°53’18.04”W, 187m from sea level).

Irrigated test were located at EVS and TVS sites, and rainfall tests at GCS and EVS (Table 1). Soil descriptions for each experimental site are as follow: EVS irrigated, Coarse-loamy, siliceous, subactive, thermic Plinthic Paleudults; EVS rainfall, Fine-loamy, kaolinitic, thermic Typic Kanhapludults; TVS, Fine, kaolinitic, thermic Rhodic Paleudults; and GCS, Fine-loamy, siliceous, subactive, thermic Plinthic Paleudults. The experimental design was a randomized complete block design with six nitrogen (N) treatments (0, 56, 112, 168, 224, 280 kg ha^{-1})

applied at planting. The corn hybrid was a Pioneer 31P42 for all sites. Plots size was 10 x 3.66m (four rows, 0.9 m between rows).

Table1. Planting and sensing date by year and location.

Year	Location	Platig Date	Sensing Date		
			V6	V8	V10
2010	EVS_BT	31-Mar	-	18-May	-
	EVS_ST*	13-Apr	18-May	-	-
	GCS	29-Mar	28-Apr	10-May	24-May
	TVS*	2-Apr	13-May	-	4-Jun
2011	EVS*	7-Apr	-	23-May	3-Jun

Irrigated (*)

Data of spectral reflectance, chlorophyll (Chl) content and leaf area index (LAI) were collected at the V6, V8, and V10 corn growth stages. All readings were collected from the two middle rows of each plot. Data of Chl content and LAI were collected as ground truth measurement for plant status. Spectral reflectance data was measured using the GreenSeeker (Trimble, Sunnyvale, CA, USA) and CropCircle ACS-470 (Holland Scientific, Inc, Lincoln, NE) remote sensors. GreenSeeeker was calibrated to measure NDVI and CropCircle for Red (670nm), near infrared (NIR, 760nm), and Red-edge (RE, 730nm) wavelengths. The sensors were run through the plots mounted on a structure based on a tuned bicycle with two extra side-wheels and a mast where the sensors were placed. The bicycle was pulled and pushed at walking speed across the plots. Leaf chlorophyll content was assessed using a Chlorophyll Meter SPAD-502 (Minolta.CO). Ten SPAD reading per plot consisting of three readings per leaf, were collected from the most recently collared leaf on each of those ten plants. Leaf area index was determined by collecting five readings per plot with the LAI-2200 plant canopy analyzer (LI-COR Biosciences).

In addition to the NDVI collected by the GreenSeeker, ten extra vegetation indices were calculated using data from Crop Circle including NDVI, red-edge NDVI (NDRE), simple ratio (SR), simple ratio red-edge (SR[RE]), inverse simple ratio (ISR) inverse simple ratio red-edge (ISR-NDRE), Carter and Miller index (CSM), Carter and Miller red-edge index (CSM-RE), chlorophyll index red-edge (CI-RE), and Modified Datt index (Datt) (Table 2). Data was standardized to zero mean and one unit variance previous calculation of the vegetation indices.

Table 2. Vegetation Indices (VIs).

Name	Equation	Reference
NDVI	(NIR-Red)/(NIR+Red)	Rouse et al. (1973), Tucker (1980)
NDRE	(NIR-RE)/(NIR+RE)	Gitelson, A.A. and M.N. Merlyak, (1994)
SR	NIR/Red	Jordan, (1969)
SR (RE)	NIR/Red edge	-
ISR	(1-NDVI)/(1+NDVI)	Gong et al., (2003)
ISR (NDRE)	(1-NDRE)/(1+NDRE)	-
CSM	Red/NIR	Carter and Miller, (1994)
CSM (RE)	RE/NIR	-
Cl (RE)	(NIR/RE)-1	Gitelson et al., (2003b) and Gitelson et al., (2005)
Datt	(NIR-RE)/(NIR-Red)	Datt, (1999)

Red= 670. RE=730. NIR=760

A canonical correlation analysis (CCA) by year, location and growth stage was conducted to identify the VIs best correlating with field-measured crop status variables. The CCA examines the relationship between two set of variables or canonical variates (X and Y) which are the result of from the linear combination of original variables within each set. For every canonical variate, the loadings of each original represent their contribution or correlation to the canonical variate Plant status canonical variate (PSV) and vegetation index canonical variate (VIV) were designated as the canonical variates for the CCA. Plant status canonical variate results from the linear combination of ground truth measurement (LAI and SPAD) and VIV outcome from the linear combination of the eleven VIs. Wilkes-Lambda statistic was used to assess the level of significance ($P<0.05$) of the canonical correlation between the variates variables in the CCA.

RESULTS

Canonical correlation analysis

The CCA usually computes more than one pair of canonical varieties, however, for this study two pairs of canonical variates were generated with the first pair having the highest significant one (P<0.05, Wilks' Lambda). Statistics associated with the CCA calculated by year-site-growth stage are shown in table 2. Because for the second pair of canonical varieties, the correlation did not reach the desired level of statistical significance (<0.05), only results associated with the first pair are presented.

The first pair of canonical variates (CC1), PSV and VIV canonical variates, was significant for all year-site-growth stages combinations with only one exception, (TVS-2010-V6) with p= 0.0687 (Table 3). Data from CC1 (eight site-year-growth stages) suggest that components of the PSV canonical variate (Chl content and LAI [proxy for canopy biomass]) could be indirectly assessed through the use of VIs.

Table 3. Canonical Correlation by year, site and growth stage.

Year	Site	GS	Canonical Correlation				Wilk's Lambda
			CC1	Pr>F	CC2	Pr>F	Pr>F
2010	EVS	V8	0.910	0.004	0.643	0.350	0.0042
	EVS*	V6	0.907	0.047	0.821	0.162	0.0472
	GCS	V6	0.948	0.000	0.714	0.157	0.0001
		V8	0.879	0.033	0.555	0.627	0.0331
		V10	0.950	0.001	0.857	0.048	0.0009
	TVS*	V6	0.861	0.069	0.710	0.295	0.0687
		V10	0.980	<0.0001	0.727	0.247	<0.0001
2011	EVS*	V8	0.933	<0.0001	0.506	0.499	<0.0001
		V10	0.921	<0.0001	0.635	0.011	<0.0001

*Irrigated. CC=canonical correlation. GS= Growth stage

Relationship between PSV and field measured variables of SPAD and LAI

The loadings of LAI and SPAD, used to evaluate the contribution or correlation of those variables to the canonical variate PSV are reported in Table 4. The higher loading of the SPAD variable (proxy for Chlorophyll content) indicated a higher contribution/correlation than LAI with the PSV canonical variate at all corn growth stages. Moreover, SPAD correlations were higher than 0.95 for all site-years at the V6 growth stage suggesting the higher dependency of early growth stages measurements on Chl content. In contrast, LAI seemed to contribute with a very low weight (<0.2 correlation) to the PSV canonical variates calculated from the data collected at the V6 growth stage in 2010. However, as the corn growth progresses in stages up to the V10 stage there is a significant increase in correlation of LAI with correlation coefficients of 0.42 and 0.62 for the GCS and TVS locations in 2010, respectively. For EVS location in 2011, a slightly negative increase in correlation of (-0.23) was observed. The results of increasing LAI correlations with growth stage for the various PSV canonical variates were expected since the plants have very low biomass at early corn growth stages. Leaf area index become important at later corn growth stages when the area between rows is mostly covered by leaves. In summary, because sensor measurements are more affected by Chl content than LAI, VIs exhibiting higher correlations with PSV are better indicators to assess Chl content variability for VRA-N.

Table 4. Canonical Correlation between original variables and PSV by year-site-growth stage

	2010							2011	
	TVS		EVS*	EVS	GCS			EVS*	
	V6	**V10**	**V6**	**V8**	**V6**	**V8**	**V10**	**V8**	**V10**
	PVS	*PVS*	*PVS*	*PVS*	*PVS*	*PVS*	*PVS*	*PVS*	*PVS*
Correlation between field-measured plant status and Plant status cononical variate.									
SPAD (Chl)	0.98	0.98	0.83	1.00	1.00	0.97	1.00	0.97	0.99
LAI	0.07	0.62	-0.2	0.73	0.08	0.73	0.46	0.12	-0.2
Correlation between vegetation indices and Plant Status canonical variate.									
GS_ NDVI	-	0.55	0.23	0.87	0.68	0.65	0.82	0.7	0.7
NDRE	0.73	0.64	0.42	0.81	0.77	0.6	0.91	0.82	0.89
NDVI	0.68	0.34	0.36	0.83	0.71	0.63	0.26	0.7	0.86
SR	0.67	0.38	0.37	0.77	0.7	0.61	0.7	0.69	0.84
SR (RE)	0.73	0.69	0.42	0.8	0.77	0.59	0.91	0.8	0.89
ISR	-0.7	-0.4	-0.4	-0.8	-0.7	-0.6	-0.2	-0.7	-0.9
SR (NDRE)	-0.7	-0.6	-0.4	-0.8	-0.8	-0.6	-0.9	-0.8	-0.9
CSM	-0.7	-0.4	-0.4	-0.8	-0.7	-0.6	-0.7	-0.7	-0.9

CSM (RE)	-0.7	-0.6	-0.4	-0.8	-0.8	-0.6	-0.9	-0.8	-0.9
CI (RE)	0.73	0.69	0.42	0.8	0.77	0.59	0.91	0.8	0.89
Datt	0.63	0.23	0.28	0.77	0.85	0.57	0.88	0.89	0.88

*Irrigated.

Relationship between PSV and VIS

Understanding the correlations between each VI and the PSV canonical variate is crucial to identify the VIs better explaining the variability in Chl content and biomass; therefore, it could be used for indirect assessment of plant status. Results from the correlation between each VI and PSV are shown in table 3. By looking at these results it is possible to evaluate the performance of each VI in assessing biomass and Chl content.

An overall trend in correlation between VI and PSV is shown across growth stages in table 3. There is a significant increase in correlation between each VIs and PSV from V6 to V10 corn growth stage. These results were expected since plants do not have enough leaves to cover the whole sensing area at early growth stages and sensor readings are ineffective due to bare soil reflectance. In contrast, at V10 most of the soil area between plants in the row and between rows is covered by leaves or plant biomass.

Correlations range from 0.23 to 0.91 at V6 and V10 respectively. The higher correlations were found in VIs containing the red edge (RE) wavelength with significant differences at early growth stages. For instance, in six from eight year-site-growth stage NDRE was higher than GS-NDVI. Differences in benefit to NDRE at V6 were 0.19 and 0.09 in EVS*-2010 and GCS-2010 respectively. At V8 only one (EVS*-2011 with 0.12 difference) of three year-site-growth stage resulted in higher NDRE. On the other two year-site-growth stage remaining at V8, higher NDVI correlations were found. Comparing the same indices at V10, NDRE show a better correlation in TVS-2010, GCS-2010 and EVS-2011 with 0.3, 0.65 and 0.03 correlation difference respectively. Results show that NDRE tend to have higher correlations at V6 and also that those high correlations had certain consistency over growth stages until the V10. Other indices containing red-edge like SR-RE, ISR-NDRE, CSM-RE, and CI-RE resulted on similar patterns yielding higher correlations that GS-NDVI in most growth stages. Observed results suggest that VIs containing red edge seems to be more sensitive to LAI and SPAD. At V8 non mayor differences were found in rainfall experiment at EVS and GCS 2010. Nevertheless, differences in 0.1 unit correlation show a better performance of RE VIs in EVS*-2011 irrigated experiment. Observed results suggest that VIs containing red edge seems to be more sensitive to LAI and SPAD in all corn growth stages.

CONCLUSION

Ten vegetation indices were evaluated for their ability to indirectly assess biomass and Chl content. The use of CCA allowed the combination of multiple variables into canonical variates to evaluate the correlation between PSV and VIV. Also PSV permitted the combination of ground truth measurement which was very important to understand plant status using a single variable. High correlations were found between canonical variates suggesting that VIs were successful assessing biomass and Chl content. Also, correlations between each independent VI and PSV were useful to found the VIs better performing at early growth stages. Vegetation indices that include red-edge wavelength resulted in an overall higher correlation than others. Since higher correlations were consistent across all growth stages, (V6 to V10) VIs containing red-edge have the potential to be utilized in VRA-N.

REFERENCES

ACES. Alabama Cooperative Extension Systemes. 2012 Corn production. P.L Mask, C.C Mitchell, Jr. http://www.aces.edu/dept/grain/cornPRO.php.

Hollinger S.E. and R.G. Hoeft. 1986. Influence of weather on year-to-year yield response of corn to ammonia fertilization. Agron. J. 78:818-823.

Huang W. 2007. Impact of rising natural gas prices on U.S. ammonia supply. www.ers.usda.gov.

ISUE. Cooperative Extension Service, Iowa State University of Science and Technology, Ames, Iowa. 1997. Nitrogen fertilizer recommendations for corn in Iowa. Pm-1714. http://www.extension.iastate.edu/publications/pm1714.pdf.

Kitchen N.R.,* K.A. Sudduth, S.T. Drummond, P.C. Scharf, H.L. Palm, D.F. Roberts, and E.D. Vories. 2010. Ground-Based Canopy Reflectance Sensing for Variable-Rate Nitrogen Corn Fertilization. Agron. J. 102:71–84. doi:10.2134/agronj2009.0114.

Miao Y., D.J. Mulla, G.W. Randall, J.A. Vetsch, and R. Vintila. 2009. Combining chlorophyll meter readings and high spatial resolution remote sensing images for in-season site-specific nitrogen management of corn. Precision Agric. 10:45–62. doi 10.1007/s11119-008-9091-z.

Mullen R.W.,* K.W. Freeman, W.R. Raun, G.V. Johnson, M.L. Stone, and John B. Solie. 2003. Identifying an in-season response index and the potential to increase wheat yield with nitrogen. Agron. J. 95:347–351.

NOAA. Satellite and information Service. 2009. http://www.osdpd.noaa.gov/ml/land/gvi.html#NDVI.

Raun W.R. *, and Gordon V. Johnson. 1999. Improving nitrogen use efficiency for cereal production. Agron. J. 91:357–363.

Raun W.R.*, J.B. Solie, G.V. Johnson, M.L. Stone, R.W. Mullen, K.W. Freeman, W.E. Thomason, and E.V. Lukina. 2002. Improving nitrogen use efficiency in cereal grain production with optical sensing and variable rate application. Agron. J. 94:815–820.

Roberts D.F., N.R. Kitchen, K.A. Sudduth, S.T. Drummond, and P.C. Scharf. 2010. Economic and environmental implications of sensor-based nitrogen management. Better Crops. Vol.94.No.1.

Seelan S.K.*, S. Laguette, G.M. Casady, and G.A. Seielstad. 2003. Remote sensing applications for precision agriculture: A learning community approach. Remote Sens. Environ. 88 (2003) 157–169. doi:10.1016/j.rse.2003.04.007

Setiyono T.D., H. Yang, D.T. Walters, A. Dobermann, R.B. Ferguson, D.F. Roberts, D.J. Lyon, D.E. Clay, and K.G. Cassman*. 2011. Maize-n: a decision tool for nitrogen management in maize. Agron. J. 103:1276–1283. doi:10.2134/agronj2011.0053.

Shanahan J.F.*, J.S. Schepers, D.D. Francis, G.E. Varvel, W.W. Wilhelm, J.M. Tringe, M.R. Schlemmer, and D.J. Major. 2001. Use of remote-sensing imagery to estimate corn grain yield. Agron. J. 93:583–589.

Shanahana J.F.*, N.R. Kitchenb, W.R. Raunc, and J.S. Schepersa. 2007. Responsive in-season nitrogen management for cereals. Comput Electron Agric 61 51–62. doi:10.1016/j.compag.2007.06.006.

Solari F., J. Shanahan,* R. Ferguson, J. Schepers, and A. Gitelson. 2008. Active sensor reflectance measurements of corn nitrogen status and yield potential. Agron. J. 100:571–579. doi:10.2134/agronj2007.0244.

Solari F., J.F. Shanahan,* R.B. Ferguson, and V.I. Adamchuk. 2010. An active sensor algorithm for corn nitrogen recommendations based on a chlorophyll meter algorithm. Agron. J. 102:1090–1098. doi:10.2134/agronj2010.0009.

Solie J.B., A.D Monroe, W.R. Raun,* and M.L. Stone. 2012. Generalized algorithm for variable-rate nitrogen application in cereal grains. Agron. J. 104:378–387. doi:10.2134/agronj2011.0249.

Stone K.C., C.R. Camp, E.J. Sadler, D.E. Evans, and J.A. Millen. 2010. Corn yield response to nitrogen fertilizer and irrigation in the southeastern coastal plain. American society of agricultural and biological engineers ISSN 0883-8542. Vol. 26(3): 429-438.

Sullivan D.G., J.N. Shaw, P.L. Mask, D. Rickman, J. Luvall and J. M. Wersinger. 2005. Evaluating corn nitrogen variability via remote-sensed data. Communications in soil science and plant analysis. 35:17-18, 2465-2483.

Teal R.K., B. Tubana, K. Girma, K.W. Freeman, D.B. Arnall, O.Walsh, and W.R. Raun*. 2006. In-season prediction of corn grain yield potential using normalized difference vegetation index. Agron. J. 98:1488–1494. doi:10.2134/agronj2006.0103.

Thorp K.R., B.L. Steward, A.L. Kaleita, and W.D. Batchelor. 2008. Using aerial hyperspectral remote sensing imagery to estimate corn plant stand density. American Society of Agricultural and Biological Engineers ISSN 0001-2351 311. Vol. 51(1): 311-320.