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COMPARISON BETWEEN HIGH RESOLUTION SPECTRAL INDICES AND SPAD METER ESTIMATES OF NITROGEN DEFICIENCY IN CORN

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Abstract. *Low altitude remote sensing provides an ideal platform for monitoring time sensitive nitrogen status in crops. Research is needed however to understand the interaction between crop growth stage, spatial resolution and spectral indices derived from low altitude remote sensing. A TetraCam camera equipped with six bands including the red edge and near infrared (NIR) was used to investigate corn nitrogen dynamics. Remote sensing data were collected during the 2013 and 2014 growing seasons at four different sites in Waseca and Wabasha counties in Minnesota. At each of the four sites, experimental plots received different rates of nitrogen varying between 0 and 200 kg/ha and imagery was collected during corn growth stages V6, V10 and R6 at six cm spatial resolution. Ancillary data collected included SPAD readings, leaf N, biomass, and yield. Preliminary results show that, among the spectral bands and indices compared, combining the green and NIR bands into a green difference vegetation index (GDVI) had the highest correlation with nitrogen application rates, SPAD reading and yield. The GDVI index was used to compute a nitrogen sufficiency index (NSI). The correlation between nitrogen application rates and GDVI was higher (r=0.80) at early growth stages (V6) than later in the season. On the other hand, the correlation between yield and GDVI was highest at the end of the growing season (r = 0.75). High resolution remote sensing can accurately detect nitrogen deficiency early in the season, leading to timely correction.*

Keywords: *Remote sensing, nitrogen deficiency, corn, spectral indices.*

Introduction

There are critical stages in corn development and growth where plant uptake of nitrogen is the most critical (Figure 1) and thus nitrogen availability is crucial. Nitrogen is usually supplied to plants in the form of a commercial fertilizer, although soil mineralization can provide a significant portion of plant's nitrogen needs (Thorne, 1926; Ruffo *et al.* 2015). Manure is also used as a source of nitrogen for farmers with livestock operations. However, commercial nitrogen fertilizer remains the dominant source of nitrogen fertilizer in the Midwest (Erickson and Miller, 2013).

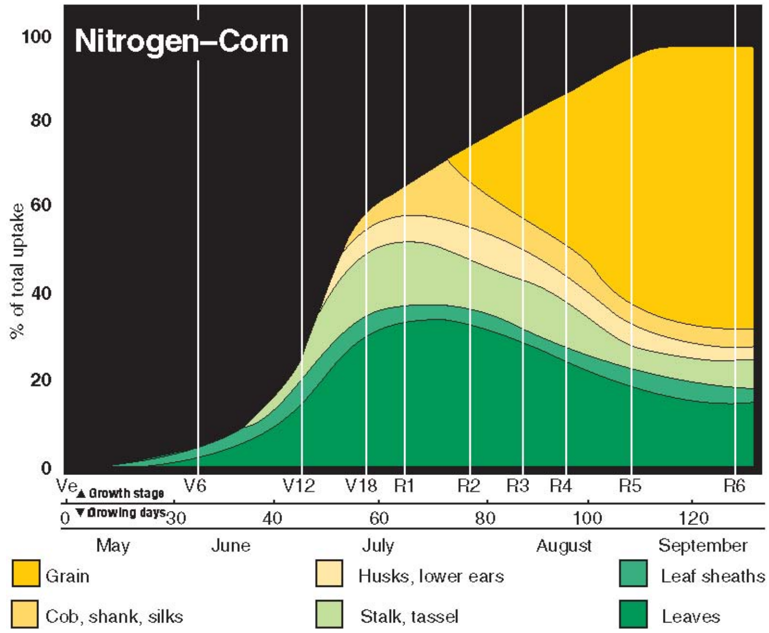

Fig.1 Critical stages of nitrogen uptake by corn (Richie et al., 1993)

Nitrogen availability and uptake by plants is very complex and controlled by many factors including weather conditions (Pinter *et al.,* 2003). In addition to the financial loss, when applied nitrogen is not used by corn plants (Smith *et al*. 2014), excess nitrogen beyond the root zone can leach from the soil profile and contribute to ground and surface water pollution (Randall and Mulla, 2001). Nitrogen is also subject to loss via denitrification under anaerobic conditions when soils are saturated long enough (Zak and Grigal, 2001). Other forms of nitrogen loss related to poor management include volatilization, for example, when nitrogen fertilizer is surface applied without incorporation in the soil (Jones *et al*. 2007).

Nitrogen management strategies that minimize the impact of inter-seasonal variation in weather conditions in rain-fed regions are needed in order to improve nitrogen use efficiency and reduce nitrogen loss to the environment. Specifically, wet springs in Minnesota are known to cause nitrogen losses via leaching and denitrification (Zak and Grigal, 2001) especially that a significant number of growers apply nitrogen in the fall (Bierman et al., 2012). One management strategy to address this issue would be to use a split application providing a portion of the nitrogen required by the crop before planting (or at planting) and the remaining portion during the growing season (in-season).

Nitrogen management can be further improved if the second nitrogen application is calculated based on remote sensing (Hatfield, 2008; Zhang and Kovacs, 2012; Tremblay et al., 2014). Of particular interest to this study is to use multi-spectral high resolution imagery as the basis for in-season nitrogen application. This type of remote sensing has the advantage of flexibility both in time and sensor technology. It is also not affected by clouds as opposed to satellites (Hunt et al., 2013).

Vegetation indices derived from satellite remote sensing such as the ubiquitous normalized difference vegetation index (NDVI) (Tucker, 1979) and the green normalized difference vegetation index (GNDVI) (Shanahan et al., 2001) have been successfully deployed to map vegetation and crop health. The GNDVI was found to positively correlate with nitrogen status in corn (Shanahan et al., 2001), and it is computed using the near infrared (NIR) and green bands reflectance. The green band reflectance supply information about the chlorophyll in the leaf as nitrogen is known to be associated with chlorophyll. On the other hand, the NIR reflectance provided information about the cell structure as healthy leaves tend to reflect more NIR (Slatan et al., 2001). Research is needed however to understand the interaction between crop growth stage, spatial resolution and spectral indices derived from low altitude remote sensing.

The first objective of this study is to evaluate the application of high resolution multispectral remote sensing for nitrogen deficiency detection in corn by comparing indices derived from UAVs with SPAD readings. A second objective is to evaluate the potential use of UAV derived indices for sidedressing nitrogen.

Materials and Methods

The experimental design for the study was randomized complete block (RCB) with four replications (Figure 2). The RCBD is a very popular design in agricultural research as it provides a powerful mean of controlling field variability and thus reducing the experimental error (Clewer et al. 2001). Preplant nitrogen treatments were conducted as a factorial with seven rates corresponding to 0, 30, 60, 90, 120, 150 and 180lb/ac of nitrogen. The treatment plan for the sidedress study was a 2 by 2 factorial corresponding to two sidedress rates of 60 and 90 lb/ac and two application times corresponding to V6 and V12 of corn growth stages. The study was replicated in four field locations in Minnesota, USA in 2013 and 2014 growing seasons. Two of the four locations had a clay loam soil texture on a glacial till deposit in south central MN (Janesville, 2013 and New Richland, 2014). The other two fields were located on a silty loam texture in eastern part of the state (Theilman, 2013 and St Charles 2014). Soil organic matter and soil residual nitrogen (spring before planting) were measured before planting for each plot and were used as covariates to correct for potential uncontrolled source of variation.

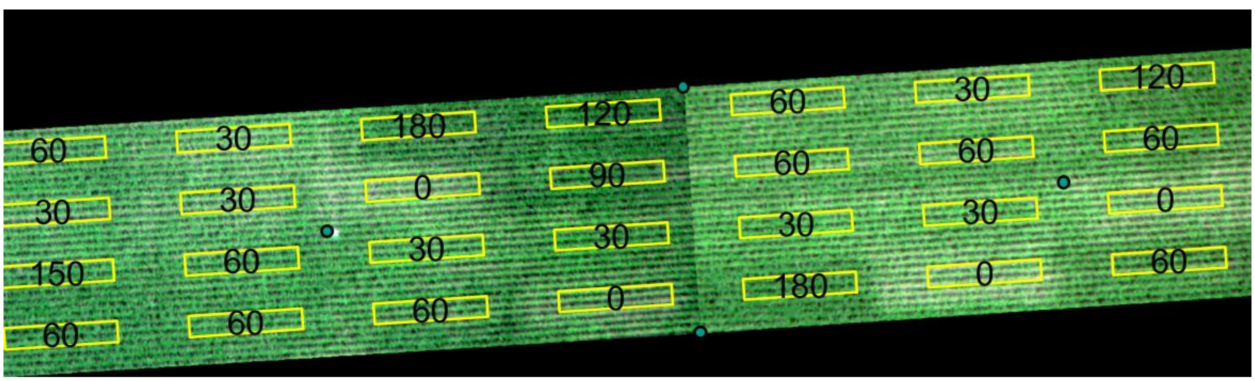

Fig. 2 UAV image showing individual plots from two adjacent blocks

At each of the three corn growing stages V6, V12 and R2, SPAD chlorophyll meter readings (SPAD Plus 502, Minolta) were collected from 20 plants within each plot and averaged. Spectral data was collected using an Octocopter equipped with a six-bands multispectral camera (MCA, Tetracam Inc, CA USA) providing plant reflectance in the blue, green, red, red edge, and near infrared (NIR) of the light spectra. The Octocopter was flown in autonomous mode using Mission Planner software. To further control the variability between plots, each of the four blocks in each site was captured in one image so that any bias introduced from flying and imagery stitching can be captured in the block effect.

Furthermore, to reduce edge effects, only reflectance data collected from the central four rows of each plot were used. At the end of the growing season, leaf nitrogen content, total biomass, and yield were also measured for each plot. Yield data were used to develop the nitrogen yield response curve for each of the location and to extract yield values that correspond to the economic optimum nitrogen rate (EONR). ArcGIS (ESRI) was used to process the multi-spectral imagery. Processing included registering the six bands, georeferencing and extraction of the spectral data for each plot within the RCB.

Soil background was removed using the histogram method by finding threshold values that allow the separation of the plant from the soil. Image segmentation was conducted on V6 corn growth stage imagery where the soil background is visible. Indices were converted to relative sufficiency indices (Hatfield, 2008; ; Sambroski et al., 2009) to minimize the effect of the environment (Debaeke et al. 2006; Lemaire et al., 2008; Sambroski et al., 2009), and to allow comparison of different fields and growth stages.

Results and Discussion

Economically optimum nitrogen rate (EONR)

Nitrogen yield response using a quadratic fit with plateau (Cerrato and Blackmer, 1990) allowed the computation of the EONR using 0.10 ratio for price of one pound of nitrogen to the price of one bushel of corn produced. Table 1 shows that the locations with heavy textures (Janesville and New Richland) had higher EONR compared to the light textured locations. Similar findings were published in a meta-analysis study conducted in the Midwest (Tremblay et al., 2012) and more recently by the Purdue University extension (Camberato and Nielson, 2016).

Table 1: The EONR for the four locations of the study

Location	EONR
Janesville 2013	116
Theilman 2013	150
St. Charles 2014	159
New Richland 2014	137

SPAD correlation with nitrogen

Previous research has shown a strong correlation between leaf nitrogen content and chlorophyll content (Piekelek and Fox, 1992; Matsunaka et al., 1997) and SPAD sufficiency index has been found to correct for genotype and environment effect (Debaeke et al. 2006).

In this study, the strength of the correlation between indices and SPAD measurements was used as a mean to compare spectral indices. The assumption is that SPAD measurements are related to chlorophyll in corn leaves and thus to nitrogen. When SPAD was not well correlated with nitrogen treatment as is the case for Janesville at V6, further investigation revealed a strong block effect (linear regression was fitted using the four replicates). Overall SPAD showed a strong correlation with preplant nitrogen and the correlation was the strongest at corn reproductive stage R2. One could also limit the use of SPAD correlation to blocks where yield response to nitrogen was strong, filtering out blocks that show a weak response to nitrogen.

This could be followed by developing spectral sufficiency indices based on data from the remaining responsive blocks. A similar approach was used by Holland and Schepers (2010) where the authors reduced the number of blocks based on block behavior. In this study however, all blocks were used to compute the correlation. It is worth stating that the correlation was stronger when each block was treated separately.

Table 2: Correlation between SPAD chlorophyll reading and preplant nitrogen.

Location	V6	V12	R2
Janesville 2013	0.66	0.80	0.73
Theilman 2013	0.78	0.77	0.83
St. Charles 2014	NA	0.84	0.88
New Richland 2014	NA	0.84	0.82

Index comparison

Several indices were computed and compared based on their correlation with SPAD (Figure 3). Among these indices, the NDVI performed very well early in the season at V6 but shortly weakened at growth stages V12 and R2. These finding corroborate similar findings that showed NDVI to saturate in mid-season (Hatfield et al., 2010). On the other hand, the green difference vegetation index (GDVI) performed better than the NDVI during all growth stages for all sites (data not shown). Additionally, index performance was stage dependent with the highest performance observed at V6 and R2 for the majority of indices.

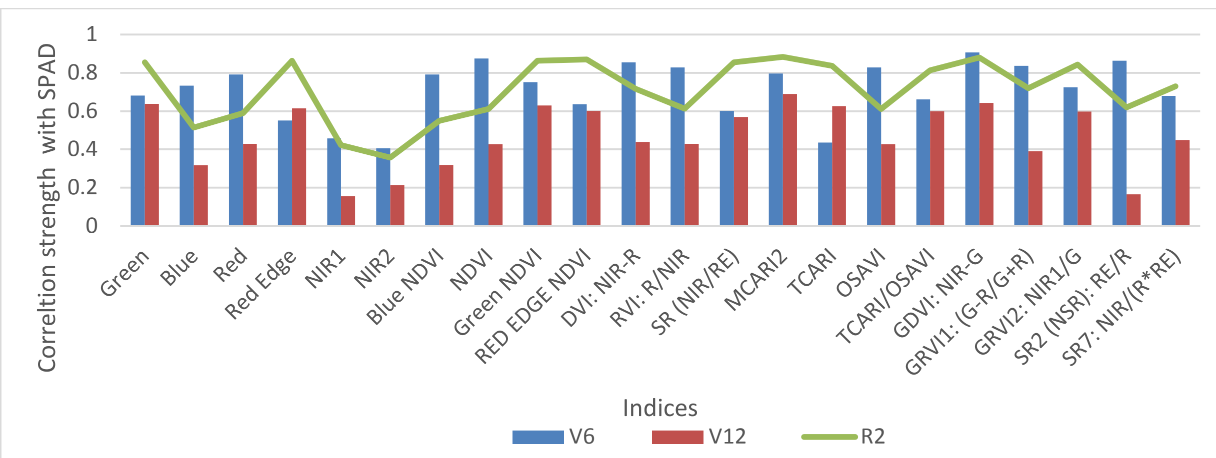

Fig.3 Correlation between UAV derived indices and SPAD meter at V6, V12 and R2, Theilman 2013

Spatial resolution and resampling

High spatial resolution images require huge storage space and processing time for operations such as stitching can be long. In this study we compared the raw resolution of 7 cm to a resampling resolution of one meter using bilinear interpolation (Table 3). Resampling to a coarser resolution does not seem to affect the correlation. This provides advantages in processing speed and storage size.

Table 3: Resampling and resolution effect on indices correlation strength with yield at V12 for St. Charles

Reflectance Indices	7cm	30cm	50cm	meter
Green	0.69	0.69	0.70	0.69
Blue	0.48	0.48	0.49	0.49
Red	0.67	0.68	0.67	0.68
Red Edge	0.63	0.63	0.63	0.63
NIR1	0.24	0.23	0.22	0.22
NIR2	0.18	0.19	0.18	0.17
Blue NDVI	0.50	0.51	0.51	0.50
NDVI	0.69	0.70	0.68	0.69
Green NDVI	0.75	0.76	0.76	0.74
RENDVI	0.70	0.70	0.70	0.69
DVI	0.72	0.73	0.71	0.72
RVI	0.69	0.70	0.69	0.70
NSI (RVI)	0.52	0.53	0.50	0.51
SR	0.67	0.67	0.67	0.66
MCARI2	0.52	0.53	0.51	0.54
TCARI	0.34	0.34	0.32	0.31
OSAVI	0.69	0.70	0.68	0.69
TCARI/OSAVI	0.68	0.69	0.69	0.68
GDVI	0.79	0.80	0.80	0.78
GRVI1	0.49	0.50	0.47	0.50
GRVI2	0.73	0.74	0.74	0.72
SR2 (NSR)	0.48	0.50	0.45	0.48
SR7	0.51	0.51	0.49	0.48

Image segmentation

One of the advantages of acquiring imagery with UAVs is the enhanced spatial resolution over satellites. The higher spatial resolution permits the separation of plant from soil background. In this study, raw images had a 7cm spatial resolution allowing for individual rows of corn plants to be identified and isolated from the soil background. The red and green bands provided the best results for soil background discrimination. Two indices GDVI and GRVI (Sripada et al, 2003) in addition to the NDVI were used to compare index correlation with yield, nitrogen treatments and chlorophyll (SPAD) before and after image segmentation (Figure 4). The results show that the correlation between the indices and yield, nitrogen applied, as well as leaf chlorophyll (SPAD) did not improve after image segmentation. For example the correlation between the amount of N applied at preplant and the GRVI decreased from 0.62 to 0.50 after soil background removal. Likewise, the correlation between SPAD and the GRVI decreased from 0.88 to 0.71 (Table 4). While this may be surprising, similar results were recently reported in Canada using a similar setup. Tremblay *et al* (2014) found no significant improvement in the correlation between SAVI and nitrogen applied after segmentation. It is possible that removing the soil background increases the importance of the biomass at the expanse of the chlorophyll. Overall, image segmentation does not seem to improve the predictability of nitrogen level in corn leaves. This finding shed lights on the need for developing new indices that can take advantage of the high resolution and image segmentation.

Table 4: Indices comparison before and after image segmentation (V6, New Richland):

	Whole Plot Correlation			**Segmented Image Correlation**		
	NDVI	**GRVI**	**GDVI**	**NDVI**	**GRVI**	**GDVI**
Yield	**0.91**	**0.62**	**0.53**	**0.74**	**0.57**	**0.52**
Applied N	**0.82**	**0.62**	**0.51**	**0.70**	**0.50**	**0.46**
SPAD	**0.78**	**0.88**	**0.84**	**0.77**	**0.71**	**0.67**

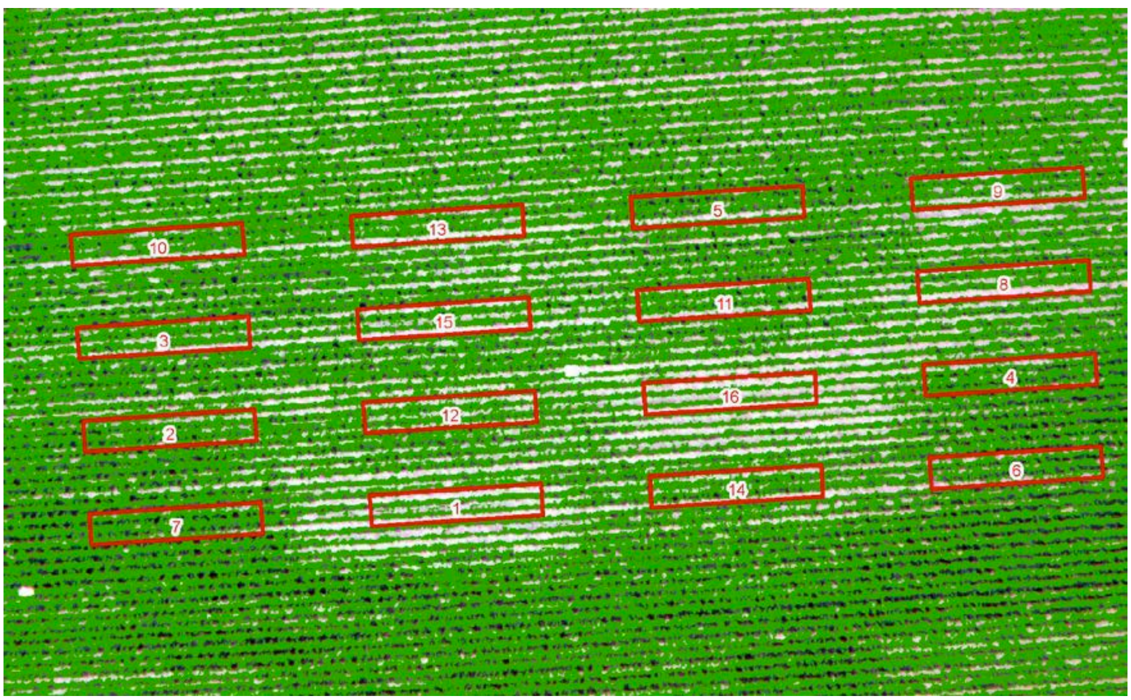

Fig.4 Segmentation based on histogram thresholding on green and red bands

Sufficiency Indices for the EONR

A nitrogen sufficiency index (NSI) was developed for each location, growth stage, and index used. The sufficiency index was computed based on the EONR. Table 5 shows the sufficiency index computed based on the GDVI for all locations.

Table 5: NSI values derived from the GDVI and the EONR

Locations	**Janesville**			**Theilman**			**St. Charles**			**New Richland**		
Stage	V6	V12	R2	V6	V12	R2	V6	V12	R2	V6	V12	R2
NSI (EONR)	0.92	0.89	0.90	0.94	0.89	0.83	0.80	0.96	0.93	0.86	0.92	0.94
NSI (Zero N)	0.72	0.74	0.70	0.70	0.74	0.73	0.45	0.60	0.65	0.50	0.63	0.73
N Recs per NSI fraction (lb/ac)	58	77	58	62	100	150	45	44	57	38	47	65

The NSI for the EONR level appears to be dynamic with both a temporal and spatial variation. This variation highlights the fact that the NSI may be field specific and thus using the virtual 0.95 reference for split nitrogen application (Holland and Schepers, 2012) may not be appropriate in this study. The NSI value was consistently lower than 0.95 across all locations (except for St. Charles at V12). The difference in NSI values between the zero N and EONR treatments is the highest for light soil likely because of the lower soil organic matter of these soils, thus resulting in a higher nitrogen requirement for similar increases in NSI values. Assuming that preplant nitrogen and sidedress nitrogen have the same impact on yield, and also assuming a linear relationship between the NSI values and the nitrogen requirements (or at least in the range between the zero nitrogen and EONR rate), one can compute the amount of in-season nitrogen required. This amount requires knowing the NSI for the zero nitrogen in addition to the NSI of the EONR. The sidedress amount will be computed based on differences in the NSI values of the EONR and zero nitrogen strips.

Implications

In-season nitrogen recommendations based on NSI are field and soil specific. Variation of the NSI highlights the fact that the NSI may be field specific and thus one cannot use the 0.95 threshold value as a benchmark for real-time nitrogen application. High resolution remote sensing can accurately detect nitrogen deficiency early in the season, leading to timely correction. Our research also shows that accuracy is not degraded with 1 meter pixel resolution, thus allowing a greater areal footprint for images.

Further investigations are underway to compare the impact of different nitrogen management strategies on NSI improvement after sidedressing. Specifically, we are looking at temporal NSI dynamics following in-season application to help understand how the split nitrogen application can correct nitrogen deficiency and potential yield.

Acknowledgements

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