Using an unmanned aerial vehicle to evaluate nitrogen variability and height effect with an active crop canopy sensor

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Using an unmanned aerial vehicle to evaluate nitrogen variability and height effect with an active crop canopy sensor

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Abstract

Ground-based active sensors have been used in the past with success in detecting nitrogen (N) variability within maize production systems. The use of unmanned aerial vehicles (UAVs) presents an opportunity to evaluate N variability with unique advantages compared to ground-based systems. The objectives of this study were to: determine if a UAV was a suitable platform for use with an active crop canopy sensor to monitor in-season N status of maize, if UAV's were a suitable platform, is the UAV and active sensor platform a suitable substitute for current handheld methods, and is there a height effect that may be confounding measurements of N status over crop canopies? In a 2013 study comparing aerial and ground-based sensor platforms, there was no difference in the ability of aerial and ground-based active sensors to detect N rate effects on a maize crop canopy. In a 2014 study, an active sensor mounted on a UAV was able to detect differences in crop canopy N status similarly to a handheld active sensor. The UAV/active sensor system (AerialActive) platform used in this study detected N rate differences in crop canopy N status within a range of 0.5–1.5 m above a relatively uniform turfgrass canopy. The height effect for an active sensor above a crop canopy is sensor- and crop-specific, which needs to be taken into account when implementing such a system. Unmanned aerial vehicles equipped with active crop canopy sensors provide potential for automated data collection to quantify crop stress in addition to passive sensors currently in use.

Keywords: Unmanned aerial vehicle (UAV), Active sensors, Imagery, Nitrogen variability, Maize

Introduction

One of the challenges with managing nitrogen (N) fertilizer is the presence of in-field spatial variability. The economically optimal fertilizer N rate (EONR), a function of yield response to N fertilizer application, can vary widely as a result (Scharf et al. 2005). The ability to detect variability in N supply within a field has been studied in depth (Kitchen et al. 2010; Roberts et al. 2010). Recent research into detecting variability in N supply has focused on non-destructive sampling techniques, which allow quantification of variability in a timely fashion and more effective in-season N management (Shanahan et al. 2008). There is a strong relationship between total chlorophyll content in a maize canopy and the N status of the crop (Dellinger et al. 2008; Barker and Sawyer 2010; Schmidt et al. 2011). As a result, non-destructive techniques have focused on remote sensing to correlate with and quantify canopy chlorophyll content. Remote sensing is used to monitor relative crop response to applied N in order to evaluate different in-season N management strategies (Scharf et al. 2011; Zillmann et al. 2006; Dellinger et al. 2008; Raun et al. 2008; Holland and Schepers 2010; Kitchen et al. 2010; Thompson et al. 2015).

Different types of sensors have been used and correlated with N stress in maize (Li et al. 2010). Remote sensing of crop canopies has predominantly used optical reflectance in the visible and NIR bands. Passive sensors are a common type of optical reflectance sensor. Passive sensors rely on the sun to illuminate the maize canopy, while active sensors use an internal light source. Each type of sensor has been documented as an appropriate way to correlate canopy reflectance with chlorophyll and N status of maize (Samborski et al. 2009; Li et al. 2010). Passive sensors require calibration and data handling techniques to account for sun angle, illumination, camera optics, rectification of imagery, and require specialized software to analyze the imagery (Berni et al. 2009).

Active sensors were developed in part to avoid the calibration requirements with regards to sunlight angle and illumination (Holland et al. 2012). Active sensors are calibrated initially in the lab, and operate independently of the sun; they may be operated day or night (Lamb et al. 2009). Currently available active sensors require close proximity to the target due to the light source intensity. Passive sensors have been used from satellites, manned aircraft and unmanned aerial vehicles (UAVs) (Berni et al. 2009). Active sensors have been vehicle-mounted, handheld or used on manned aircraft (Lamb et al. 2009). To date, active sensors have not been mounted or integrated into unmanned aerial vehicles.

Unmanned aerial vehicles have potential as a platform for detecting and managing crop stress during the growing season, and they provide unique advantages compared with other platforms (Colomina and Molina 2014). Unmanned aerial vehicles may be automated allowing information to be acquired more frequently with fewer resources than manned aircraft and can be done independent of field ground conditions.

A potential issue with mounting an active crop canopy sensor on a UAV is the proximity needed to acquire crop canopy reflectance. The close proximity needed may be restrictive for UAV flight. The hypothesis is that the ranges reported for use of the active crop canopy sensor mentioned below will facilitate a range of height that a UAV may operate effectively within to accurately collect crop canopy reflectance.

The objectives of the study were:

1. To determine if a UAV was a suitable platform for use with an active crop canopy sensor to monitor in-season N status of maize.
2. If objective 1 is true, is the UAV and active sensor platform a suitable substitute for current handheld methods?
3. Is there a height effect that may be confounding measurements of N status over crop canopies?

Methods

Three experiments were conducted over the course of 2013 and 2014 using optical sensors. Studies were conducted at two locations during the 2013 and 2014 growing seasons to evaluate the use of different sensors and platforms for detecting N rate effects on maize. In 2014, a study was conducted over turfgrass as the target to quantify the effect of height above the canopy on a UAV-mounted active sensor measuring N status.

Equipment

A modified Crop Circle RapidScan™ CS-45 active sensor (Holland Scientific, Lincoln, NE, USA) was mounted on a MikroKopter OktoKopter XL (MikroKopter, HiSystems GmbH, Moormerland, Germany) UAV platform, subsequently referred to as the Aerial Active (AA) sensor platform. The RapidScan sensor's logging method was modified to allow continuous data collection at one second intervals, in contrast with the unmodified version of the RapidScan that averages data collected between a manually triggered start and stop. The RapidScan sensor measures reflectance at 670, 730, and 780 nm from a modulated, polychromatic LED light source. The sensor includes an on-board power supply, data logger and GPS. The sensor logged position and reflectance in individual wavebands as well as calculated normalized difference red edge (NDRE) reflectance every second. The AA platform was flown manually rather than autonomously. The only input to autonomously control platform height and position was differentially corrected GPS position which, due to normal GPS error in positioning, created more variation in position vertically and horizontally than was the case with manual control.

A standard Crop Circle RapidScan™ CS-45 sensor was utilized for hand-held measurements of crop canopy reflectance in the same wavebands as AA. This sensor platform is subsequently referred to as the Handheld Active platform (HA).

Aerial imagery was acquired using a Tetracam Mini-MCA 6 band camera (Tetracam Inc., Chatsworth, CA, USA) mounted on a MikroKopter OktoKopter XL UAV platform, subsequently referred to as the Aerial Passive (AP) platform. Reflectance was collected in 6 bands, with wavelengths centered at 530, 670, 710, 760, 800, and 970 ± 10 nm. Images were taken at approximately 100 m above ground from the nadir position with a spatial resolution of 50 mm. Each image taken from the AP included a calibration panel. Calibration panels were placed at the canopy height level in each image to convert digital numbers obtained by the sensor to percent reflectance. Calibration panels, made of plywood, consisted of four shades of gray paint, tested for reflectance consistency under a calibrated halogen light source using a USB-2000 Ocean Optics spectroradiometer (Ocean Optics, Dunedin, Florida, USA) in the range from 350 to 1024 nm in 0.37 nm increments. Reflectance by waveband for calibration panels is shown in Fig. 1.

Raw images were converted to reflectance and then georectified using ArcGIS 10.0 (ESRI, Redlands, CA, USA). Reflectance for each band was obtained by first regressing the linear relationship between digital numbers obtained from the raw image over the panel target versus the known reflectance of the gray shades on the calibration panel. Remaining reflectance values for each digital number throughout the image were calculated by applying the derived linear regression relationship. Vegetation indices were calculated from individual reflectance images using the raster calculator in ArcGIS 10.0.

Maize Canopy 2013

In 2013, a subset of plots from two adjacent fertilizer N studies, one replication from each, with maize were used to collect data for a comparison of sensor platforms (HA, AA and AP). Subsets of each study were used due to logistical constraints of the AA platform: battery life and area to land and take off in proximity of treatment plots. Collecting data with the AA platform required the pilot to walk at a safe distance behind the platform while operating the AA over the treatment plots. This method decreased the amount of area that could be sensed due to battery life restrictions. The site was located at the University of Nebraska-Lincoln's South Central Agricultural Laboratory (SCAL) near Clay Center, Nebraska, USA (latitude: 40.568758°, longitude: –98.144594°). Treatments from the two replications consisted of several fertilizer N rates: 0, 112, 156 and 201 kg N ha^{-1} and N sources (urea ammonium nitrate solution (UAN), anhydrous ammonia (NH_3) and polymer-coated urea (ESN: Agrium, Inc., Calgary, AB, Canada).

Plots were 13.7 by 3.0 m with four rows on a 0.76 m on-center spacing. Canopy reflectance data were collected at V12 and R2 (Abendroth et al. 2011) growth stages. Growth stages chosen for data collection provided opportunity for the maize canopy to reflect differences in N status before and after tassel, which may interfere with sensor readings (Shanahan et al. 2001). Timings also represent potential growth stages for in-season N application via high clearance applicator or irrigation equipment.

The AA sensor collected data between the center two rows of each plot. This was done to ensure a linear data collection path since the UAV was manually controlled. The target height above the canopy for AA was 1 m.

Due to wind gusts and drafts and operator skill, actual height varied from 0.5 to 1.5 m above the canopy. The HA collected data from a height of approximately 1 m above the canopy, directly over each of the center two rows of each plot at the V12 growth stage, and between rows at the R2 growth stage to avoid tassel interference with canopy reflectance. To compare data values from each sensor platform, an average plot value for the response variable of the center two rows was calculated. The AP sensor collected data as noted previously. Vegetation indices were calculated for each sensor platform and regressed against N rate by growth stage. Vegetation indices were calculated with respect to each sensor's wavebands; active sensor systems (AA, HA) used slightly different wavebands than the passive system (AP).

Vegetation indices were regressed against N rate for each sensor using PROC REG (SAS Institute Inc., Cary, NC, USA). Both 2nd order polynomial and linear slope were tested for significance. To compare platforms, the noise equivalent was calculated for each platform throughout the range of applied N rates (Viña et al. 2011). Equation 1 illustrates the calculation of noise equivalent (NE) where RMSE is the root mean square error of the regression relationship, and the denominator is the slope of the regression prediction equation for a given change in N rate. If regression equations resulted in nonsensical responses (i.e. negative slope), those equations were discarded.

$$\text{NE}\Delta\text{N rate} = \text{RMSE (VI vs N rate)} / [\partial(\text{VI})/\partial(\text{N rate})] \quad (1)$$

Vegetation indices were chosen based on the best adjusted coefficient of determination (adj r^2) for each sensor platform. In this way, each sensor platform is represented by the most sensitive index that the sensor is capable of measuring for the dataset at a given crop growth stage. Indices used in the initial comparison to determine the best adjusted r^2 are included in Table 1. Initial indices used in comparison for each sensor platform and growth stage were chosen based on frequent citations in the literature for measuring chlorophyll content in plant canopies.

It is important to note that strong winds damaged plants between the V12 and R2 growth stages. The maize plants were lodged but not broken. Consequently, lodged plants had reduced yield potential. The canopy consisted of a heterogeneous combination of partially lodged and unaffected plants. This likely resulted in reduced yield potential and differential effects of N uptake.

A modified plot combine harvested the middle two rows of each plot. Moisture content was adjusted to 155 g kg^{-1}. Noise equivalent of yield versus N rate was computed using the same criteria detailed above for the respective VI versus N rate regression relationship by replacing VI with yield.

Maize Canopy Study 2014

A subset of plots from a fertilizer N study with maize was used to collect data for comparison of sensing platforms in 2014. The site was located near Central City, Nebraska, USA on a co-operating producer's field (latitude: 41.243154°, longitude: –98.033071°). The study was a randomized complete block design with three replications. Plots were 13.7 by 3.0 m with four rows on 0.76 m on-center spacing. Five fertilizer N rates were applied prior to planting: 0, 90, 179, 224, and 314 kg N ha^{-1} in the form of UAN, and were evaluated in July 2014. The maize canopy at time of sensing was at the V11 growth stage. Two sensing platforms were used: HA and AA as described previously. Data was analyzed using PROC REG and PROC CORR (SAS Enterprise Guide 6.1, Cary, NC, USA).

Distance Sensitivity Study 2014

There were concerns that the fluctuating height of the AA platform used in the maize studies was leading to error in measurements. Maize canopies have differences in the vertical distribution of chlorophyll concentration (Viña et al. 2011). Active sensors, dependent on the specific sensor, do not measure reflectance from the entire depth of the maize canopy, (Solari 2006). Differences in VI versus N for each sensing platform relate to what portion of the canopy was in the field of view (FOV). To investigate these issues, Kentucky bluegrass was used as a crop canopy to evaluate distance sensitivity (height above canopy) of a UAV-mounted active crop canopy sensor to detect N stress. Turfgrass provides a relatively uniform and less complex canopy architecture compared to maize to measure reflectance when changing the distance of a sensor above the canopy. Also, the sensor's light would likely interact with all of the turf canopy, compared to only a portion of the maize canopy The experiment was located on the Kentucky bluegrass turf plots at the University of Nebraska-Lincoln Agricultural Research and Development Center (ARDC), near Mead, NE, USA (latitude: 41.170904°, longitude: –96.467731°).

Urea was applied to turf plots 2 weeks prior to sensing at rates of 0, 25, 50, 75, and 100 kg N ha^{-1}, to plots of 4.6 × 4.6 m. Three passes of the AA system were conducted in June 2014 over each N rate plot at heights of 0.5, 1.0, 1.5, 2.0, and 2.5 m. Sensor data were processed in ArcMap 10.2 (ESRI, Redlands, CA, USA). A buffer of 0.76 m was used to eliminate data near the plot boundary. Cleaned data were analyzed by analysis of variance and regression, using PROC GLM, GLIMMIX and REG (SAS Enterprise Guide 6.1, Cary, NC, USA).

Results and discussion

Maize Canopy Study 2013

Noise equivalent

Table 2 contains the best fit VI for each sensor platform and the corresponding parameter estimates used in the calculation of NE. Noise equivalent varied significantly among sensor platforms (Fig. 2). Lower values of NE indicate a more sensitive relationship of the response variable to the explanatory variable. For example, the DATT index for the HA platform versus N rate had a significant 2nd order polynomial relationship at the V12 growth stage (Table 2). The slope of this relationship is steepest at low values of N rate, but as the N rate increases, the slope decreases significantly, consistent with a 2nd order polynomial relationship. The steeper the slope relative to the error in modeling that relationship, the more sensitive or lower the NE. A significant regression relationship may be compared directly against other regression relationships because each is normalized with respect to the RMSE.

At the V12 growth stage, the HA platform had the lowest NE, followed by AA and AP (Fig. 2). The HA was held over an individual row maintaining a nearly constant height FOV of the crop canopy. The AA platform, operated manually via a handheld radio controller (RC), was clearly the most variable platform for height and field of view control (FOV).The AP method integrates soil as well as crop canopy reflectance, while the active sensor methods, located directly over plant rows, do not capture soil reflectance (Ciganda et al. 2012).

It is important to note that the relationship between the AP platform and N rate, using the DATT VI, resulted in a linear relationship. In comparison to the other sensor platforms, the AP was less sensitive to N rate at the lower N rates (i.e. less than 105 kg ha^{-1}) (Fig. 2).

At the V12 growth stage, there is likely a plateau of plant response to higher N rates because the maize canopy has taken up and metabolized only a fraction of the total supplied N up to that point. In this situation, it would be more desirable to accurately model lower N rates for increased accuracy in in-season N rate recommendations.

At the R2 growth stage, the HA and AP platforms had different best fit regressions of VI versus N rate (Table 2). The HA platform had a significant linear relationship, but the AP and AA platforms both had significant 2nd order polynomial relationships to N rate (Table 2). The AP and AA sensor platforms were more sensitive (i.e. lower NE) than the HA platform when the N rate was roughly below 100 kg ha^{-1}, but at higher rates of N the HA platform was more sensitive (Fig. 2). Generally, the relationships between all platforms and N rate had higher coefficients of determination at the R2 versus V12 growth stage (Table 2). This is likely to be the cause of more of the applied N being taken up and utilized by the plant. Therefore, later in the growing season, it would likely be of benefit to detect with more sensitivity higher rates of applied N.

The NE of yield to N rate is shown in Fig. 2. This relationship was best fit with a linear plateau model (Fig. 3). Yield becomes insensitive at N rates above 112 kg ha^{-1}, where there is no relationship between yield and the remaining applied N rates. This is the plateau of yield response to applied N (Fig. 3). Vegetation indices used to predict N rate would then also become infinitely insensitive (slope of 0) to N rate if applied N rate was the only factor explaining variation in yield, but it is not. The coefficient of determination for yield versus N rate was only 0.76. The regression between yield and N rate does not provide a good fit for the relationship considering the error in the relationship, but it approximates what response there is to applied N rate, be it small in this case. It is worth noting that applied N rate and total N available to the plant are not the same. The effect of the wind-damaged canopy likely reduced yield potential and as a result uptake of N, which further degraded the relationship between yield and applied N. Wind damage also likely caused added variation in yield response to N application as shown in Fig. 3.

This study illustrates the capacity for each sensor platform to detect canopy differences with fertilizer N rate, but this limited dataset is not meant to be a predictive model for other locations. Though there are relative differences between the sensitivity of each sensor in detecting applied N rate, the relationship of applied N to canopy reflectance parameters and yield was reduced due to weather damage.

Maize Canopy Study 2014

Figure 4a illustrates the regression comparison between sensors using NDRE. The linear regression relationship was highly significant (Fig. 4a). The NDRE from AA and HA was regressed against N rate (Fig. 4b). Both relationships were significant, with an adjusted r^2 of 0.53 and 0.51 for AA and HA respectfully.

The relationships were similar to that of maize grain yield and fertilizer N rate, which was highly significant and had an adjusted r^2 of 0.55 (Fig. 4c). Though the variation between yield and fertilizer N rate indicates that other sources of variability contributed to differences in yield, the comparison between NDRE and yield explained 90 and 88 percent of the total variability for AA and HA respectively (Fig. 4d).

The relationship between AA and HA (Fig. 4a) showed that generally AA NDRE was lower than HA NDRE. This is likely because of the way data were collected with the AA versus the HA. The HA maintained a height of 1.0 m above the canopy, and the angle between the sensor and the crop canopy was kept constant. This would likely introduce less variation compared to the AA, which fluctuated in height from 0.5 to 1.5 m, despite efforts to maintain 1.0 m. The AA did not continuously maintain a constant angle relative to the crop canopy due to small directional corrections to maintain the path of the UAV. The fluctuating height is of concern as noted above due to the chlorophyll distribution in a maize canopy. If an active sensor is to be mounted to a UAV, height control and a sensor gimbal are needed to maintain height and angle relative to the crop canopy.

Results from the 2014 Maize Canopy Study showed that using AA to collect proximal sensing information is an acceptable option for in-season N management due to a high correlation between the HA and AA sensor platforms. For the 2014 Maize Canopy study, both platforms proved to be good predictors of yield when used at the V11 growth stage. However, though there was a significant relationship between yield and applied N rate, there was large variation in this relationship. This study was located on a coarse-textured soil where significant loss of applied N rate was expected, and likely the cause of small scale variability in N supply. The relationships modeled for 2014 in this study are not intended to be predictive models for other situations, but rather to illustrate the potential for AA sensor use for in-season N management.

For both the 2013 and 2014 maize canopy studies, the relationship between N rate and grain yield had significant variation. Other measurements to quantify N status were not taken. Comparing vegetation indices to applied N rate is appropriate to measure crop response, and the potential need for supplemental N during the growing season.

Distance Sensitivity Study 2014

While the 2013 and 2014 maize canopy studies illustrated the potential for AA sensor use to assess the N status of a maize canopy, there was substantial variation in the relationships between N rate, NDRE and grain yield in these studies. While weather and small scale field variation in N supply were suspected as primary sources of this variation, there was also uncertainty related to the complexity of the maize canopy reflectance, especially with unavoidable variance in sensor distance and angle. Consequently, a study was conducted in 2014 over a turfgrass canopy to better understand effects of sensor distance and angle on NDRE from a relatively uniform and flat crop canopy surface. Figure 5a shows the relationship between NDRE and N rate at different heights of the AA above the canopy. As N rate increased, NDRE increased as expected. As height increased, NDRE decreased. When the combined dataset is considered, there were no statistically significant interactions between height and N rate in their effects on NDRE (Table 3). Visually, there appeared to be different slopes for NDRE related to N rate for heights of 0.5, 1.0, and 1.5 m compared to 2.0 and 2.5 m (Fig. 5a). When individual heights, grouped heights and specific wavelength reflectance were considered, regression analysis indicated that each N rate at each height was significantly related to NDRE, but adjusted r^2 values decreased with increasing height (Fig. 5a; Table 4).

Based on visual observation of slope relationships in Fig. 5a, data were partitioned by height into two groups: 0.5, 1.0, and 1.5 m (LOW) and 2.0, 2.5 m (HIGH) for analysis (Fig. 5b). There were no significant differences in slope within groupings of LOW or HIGH, but there was a significantly different slope between these groups (Table 5). When the groups of LOW and HIGH are compared, there is no interaction of height and N rate (Table 6).

Figure 6a shows how the change in reflectance with height differs for RE, R, and NIR wavelengths; NIR reflectance decreased significantly as height increased, while RE and R reflectance remained relatively constant. Results show a relationship of vegetation index with height when the whole range of heights tested are considered. However, for a grouped range of heights (i.e. 0.5–1.5 m), the response is not statistically different.

If height is still considered, Fig. 6b illustrates the regression model by height using the same slope, but with statistical differences between each intercept noted. Other attempts to improve the relationship, i.e. multiple regression taking both N rate and height into account, had little to no effect on improving the adjusted coefficient of determination (Table 7). The difference in response to N rate as height increased is related to the NDRE calculation using red edge (730 nm) and NIR (780 nm) wavebands.

Table 7 illustrates the capacity of various data groupings to detect differences in N rate. The LOW dataset had an error of 7.4 kg N ha^{-1}, similar to the error from 0.5 m height alone. As height increased, RMSE increased to a value of 26 kg N ha^{-1} for the 2.5 m height dataset. Collectively, for this model of the RapidScan sensor (AA), maintaining a height above the crop canopy between 0.5 and 1.5 m allowed detection of N rate differences within the range of 7–10 kg N ha^{-1}.

Conclusions

The 2013 and 2014 maize datasets established the potential for use of an AA platform to evaluate in-season crop canopy N status. The 2013 Maize Canopy Study provided supportive evidence that each of the three sensor platforms tested (HA, AP, and AA) were capable of detecting N rate effects on the maize canopy. However, inconsistencies among methods, and noise equivalents for the 2013 Maize Canopy Study, prevent a conclusion as to which platform is best suited for detecting differences in canopy response to N. The 2014 turfgrass study showed that distance effects on vegetation indices are real, and the effects are likely to be sensor and crop specific. It should be noted that the sensor used in this study was originally not intended for use on a UAV. However, the AA platform used in this study, operated effectively within a range of 0.5–1.5 m above the canopy. The AA platform performed similarly to other sensor platforms, either active or passive. However, these studies only establish the potential for an AA platform for in-season N management; further research is needed to evaluate FOV and height stability issues with an AA platform, and to better establish predictive relationships between AA sensor information and the need for supplemental N. Other influences on measurement, such as interference of the crop canopy from air movement generated by the UAV at the lowest heights need to be explored.

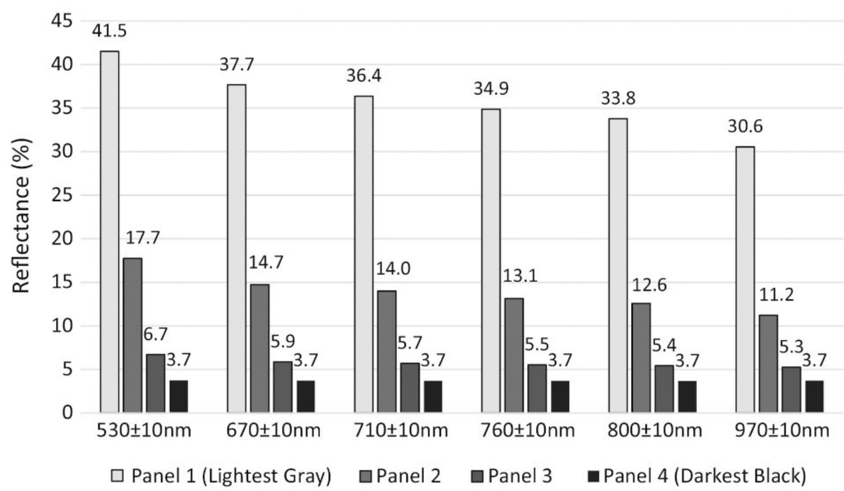

Fig. 1. Calibrated reflectance values for Tetracam MCA-6 wavebands used for the AP platform. Four shades of gray were used to accommodate typical reflectance values for a given waveband when imaging a maize canopy.

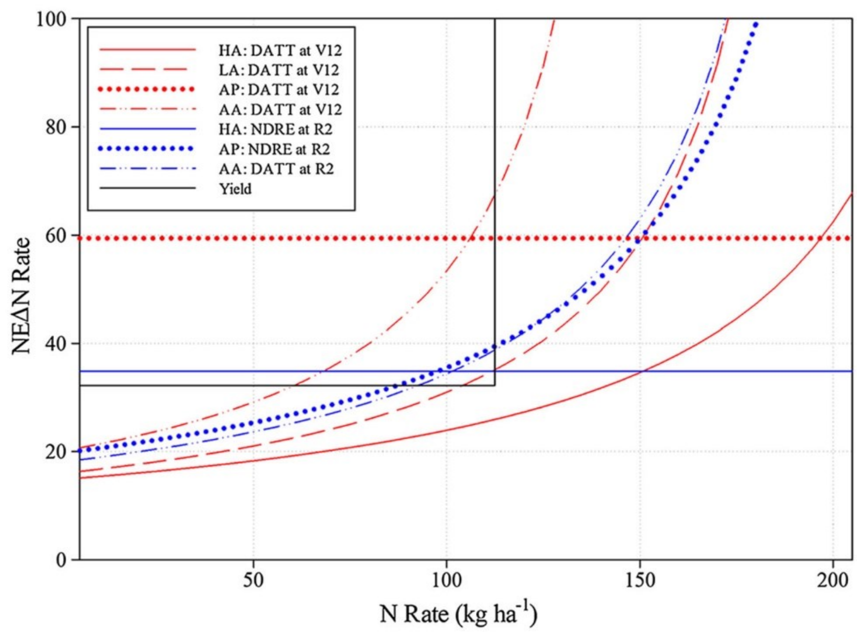

Fig. 2. Noise equivalent for the response variable versus N rate, Maize Canopy Study 2013. The response variable is either the best fit VI versus N rate for each platform by each growth stage, or grain yield versus N rate. Grain yield plateau is represented by the vertical line going beyond the scale of the *y* axis.

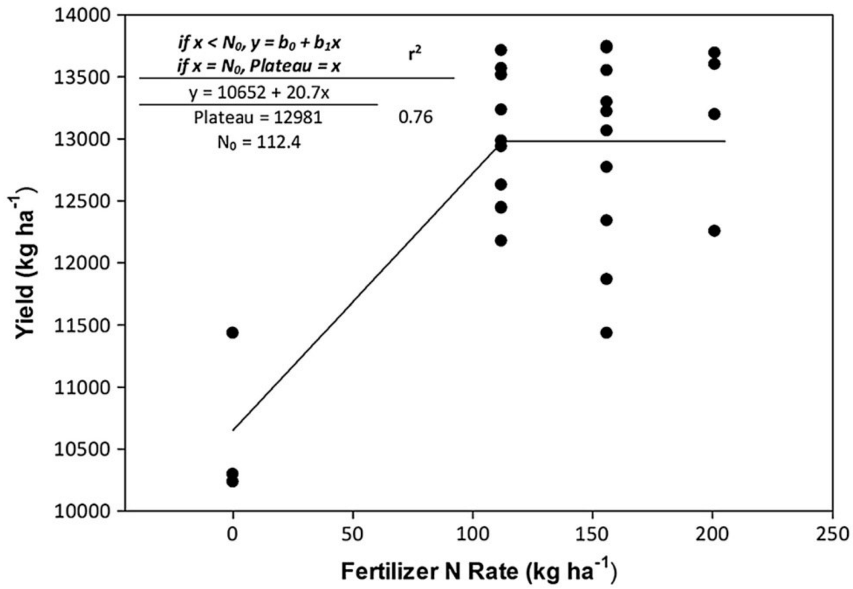

Fig. 3. Grain yield versus applied fertilizer N rate for the Maize Canopy Study in 2013. A linear plateau regression line is shown with the respective fit parameters.

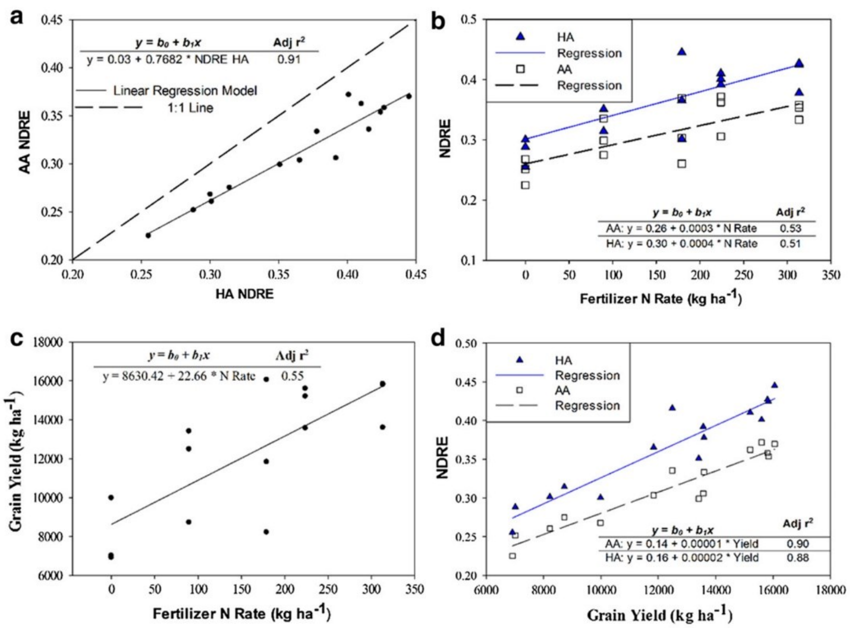

Fig. 4. a) Regression relationship of NDRE between the AA to HA platforms. A 1:1 relationship line is shown for comparison. **b)** Relationship of NDRE acquired by AA to fertilizer N rate, Maize Canopy Study 2014. **c)** Relationship of maize grain yield to fertilizer N rate. **d)** Relationship of NDRE acquired by AA to maize grain yield. Maize Canopy Study 2014.

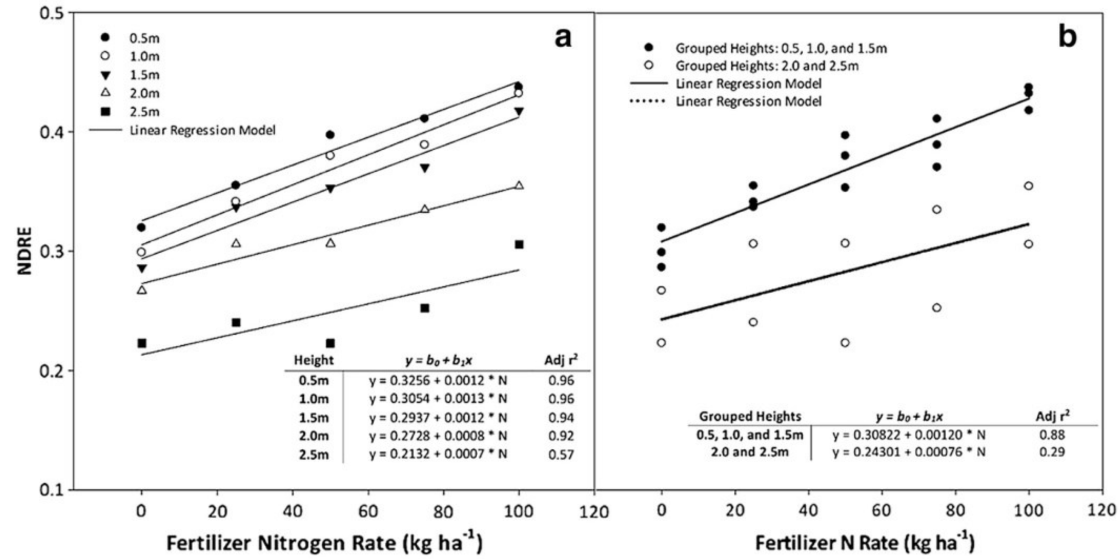

Fig. 5. a) Influence of nitrogen fertilizer rate and height above crop canopy on NDRE on the turf study. **b)** Relationships of nitrogen fertilizer rate and height above canopy in LOW and HIGH groups to NDRE, Distance Sensitivity Study 2014.

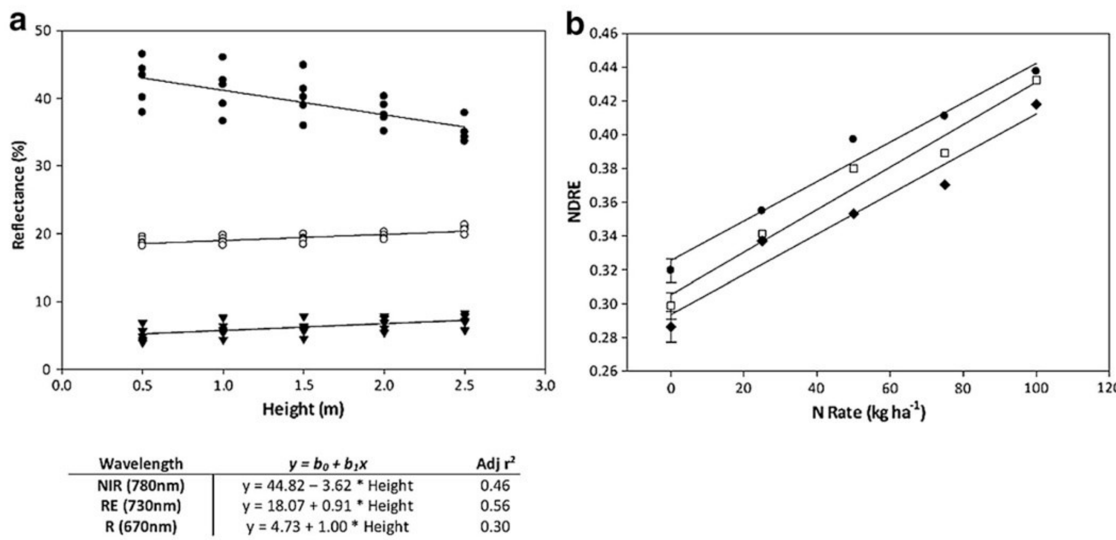

Fig. 6. a) Relationships of wavelength (RE, R, and NIR) and height above turfgrass. **b)** Relationship of LOW sample data and fertilizer N rate to NDRE, Distance Sensitivity Study 2014.

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Table 1. Selected vegetation indices and corresponding citation

Vegetation index	Index calculation	Source
SR	SR = NIR/R	Birth and McVey (1968)
NDVI	NDVI = (NIR – R) ÷ (NIR + R)	Rouse et al. (1973)
NDRE	NDRE = (NIR – RE) ÷ (NIR + RE)	Buschmann and Nagel (1993)
GNDVI	GNDVI = (NIR – G) ÷ (NIR + G)	Buschmann and Nagel (1993)
CI	CI = NIR/G – 1	Gitelson (2003)
CI RE	CI = NIR/RE – 1	Gitelson (2003)
DATT	DATT = (NIR – RE) ÷ (NIR – R)	Datt (1999)
MTCI	MTCI = (NIR – RE) ÷ (RE – R)	Dash and Curran (2004)
WDRVI	WDRVI = (a * NIR – R) ÷ (a * NIR + R)	Gitelson (2004)

The corresponding wavelengths used for AP: 530, 670, 710, and 800 nm, which is G, R, RE, and NIR respectively. Wavelengths used by both active platforms: 630, 760 and 780 nm, which is R, RE, and NIR respectively.

Table 2. Regression parameters for the Maize Canopy Study 2013 for the best fit VI versus N rate for each sensor platform

Linear models

Sensor platform	Growth stage	Model	Parameter estimates			Adj r^2	RMSE	P value
			Intercept	N rate (kg ha^{-1})	N rate^2 (kg ha^{-1})^2			
HA	V12	DATT = N rate + N Rate^2	0.58601	0.00039468	–0.00000076	0.85	0.00590	<.0001
AP	V12	DATT = N rate	0.82282	0.00017439	–	0.46	0.01036	<.0001
AA	V12	DATT = N rate + N rate^2	0.55821	0.00066553	-0.0000021	0.57	0.01355	<.0001
HA	R2	NDRE = N rate	0.39455	0.00029682	-	0.72	0.01036	<.0001
AP	R2	NDRE = N rate + N rate^2	0.75054	0.00070675	-0.0000016	0.72	0.01408	<.0001
AA	R2	DATT = N rate + N rate^2	0.58030	0.00063150	-0.0000015	0.74	0.01152	<.0001

Non-linear model

Model	Intercept	N rate (kg ha^{-1})	N_0 (kg ha^{-1})	Plateau (kg ha^{-1})	r^2	RMSE	P value
Yield = N rate if N rate < N_0	10,652	20.7	112.4	12,981	0.76	667.42	<.0001
Plateau = N rate if N ≥ N_0							

Grain yield versus N rate regression parameters are also shown under the non-linear portion of the table. The N rate at which yield plateaus is N_0. Plateau refers to grain yield.

Table 3. Analysis of variance for effects of height above canopy and nitrogen fertilizer rate on normalized difference red edge (NDRE) values, Distance Sensitivity Study 2014

Effect	Numerator DF	Denominator DF	F value	Pr>F
Height (m)	4	15	16.94	<.0001
N rate (kg ha^{-1})	1	15	181.28	<.0001
N rate × height	4	15	2.09	0.1334

Table 4. Linear regression models with corresponding parameter estimates, Distance Sensitivity Study 2014

Regression model	Height(s) grouped (m)	Adj r^2	Parameter estimates			RMSE	P Value
			Intercept	N rate (kg ha^{-1})	Height (m)		
NDRE versus N rate	0.5	0.96	0.3256	0.0012	–	0.009	0.0019
NDRE versus N rate	1.0	0.96	0.3054	0.0013	–	0.010	0.0023
NDRE versus N rate	1.5	0.94	0.2937	0.0012	–	0.012	0.0042
NDRE versus N rate	2.0	0.92	0.2728	0.0008	–	0.009	0.0059
NDRE versus N rate	2.5	0.57	0.2132	0.0007	–	0.022	0.0871
NDRE versus N rate	0.5, 1.0, 1.5, 2.0, 2.5	0.32	0.28	0.001	–	0.052	0.0020
NDRE versus N rate + height	0.5, 1.0, 1.5, 2.0, 2.5	0.89	0.38	0.001	–0.065	0.021	<.0001
NDRE versus N rate + height	0.5, 1.0, 1.5	0.96	0.34	0.001	–0.031	0.009	<.0001
NDRE versus height	0.5, 1.0, 1.5, 2.0, 2.5	0.53	0.43	–	–0.065	0.043	<.0001
NDRE versus height	0.5, 1.0, 1.5	0.01	0.40	–	–0.030	0.047	0.3123
NIR versus height	–	0.46	44.82	–	–3.621	2.749	0.0001
RE versus height	–	0.56	18.07	–	0.908	0.571	<.0001

The ''height(s) grouped'' column refers to the respective height(s) that were combined for the Height parameter.

Table 5. Analysis of variance for interactions with fertilizer N rate with either the height above canopy groupings (LOW and HIGH) or the interactions within each height grouping (LOW, HIGH)

Partitioned N rate × height group	Numerator DF	Denominator DF	F value	Pr>F
N rate × height group (LOW vs HIGH)	1	15	8.00	0.0127
N rate × height (2.0, 2.5 m)	1	15	0.19	0.6706
N rate × height (0.5, 1.0, 1.5 m)	2	15	0.08	0.9238

Distance Sensitivity Study 2014

Table 6. Analysis of variance for height above turf grass and fertilizer N rate effects on NDRE with LOW and HIGH groupings

Effect	Numerator DF	Denominator DF	F value	Pr>F
Height	2	15	4.03	0.0562
N rate	1	15	251.63	<.0001
N rate × height	2	15	0.13	0.8761

Table 7. Linear regression analysis for effects of height above crop canopy and error in prediction of N rate, Distance Sensitivity Study 2014

Regression model	Height(s) grouped (m)	Adj r^2	Parameter estimates				RMSE (kg ha^{-1})	P value
			Intercept	N rate (kg ha^{-1})	Height (m)	NDRE		
N rate versus NDRE	0.5	0.96	-270.18	–	–	833.92	7.513	0.0019
N rate versus NDRE	1.0	0.96	-233.75	–	–	770.49	7.978	0.0023
N rate versus NDRE	1.5	0.94	-233.86	–	–	804.15	9.777	0.0042
N rate versus NDRE	2.0	0.92	-312.52	–	–	1155.98	10.922	0.0059
N rate versus NDRE	2.5	0.57	-186.95	–	–	952.56	25.935	0.0871
N rate versus NDRE	0.5, 1.0, 1.5 (LOW)	0.96	-269.96	–	24.80	801.19	7.451	<.0001
N rate versus NDRE	2.0 and 2.5 (HIGH)	0.29	-86.94	–	–	487.02	31.33	0.2932
N rate versus NDRE + height	0.5, 1.0, 1.5, 2.0, 2.5	0.75	-272.07	747.20	48.58	–	18.162	<.0001