Active and Passive Sensor Comparison for Variable Rate Nitrogen Determination and Accuracy in Irrigated Corn

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Abstract. The objectives of this research were to (i) compare active and passive crop canopy sensors' sidedress variable rate nitrogen (VRN) derived from different vegetation indices (VI) and (ii) assess VRN recommendation accuracy of active and passive sensors as compared to the agronomic optimum N rate (AONR) in irrigated corn. This study is comprised of six site-years (SY), conducted in 2015, 2016 and 2017 on different soil types (silt loam, loam and sandy loam) and with a range of preplant-applied nitrogen (N) rates (PANR, 0 to 309 kg N ha^{-1}). Crop reflectance data was acquired using four different sensors: RapidScan (handheld, active) and Tetracam, MicaSense RedEdge or Parrot Sequoia (unmanned aerial system-mounted, passive). Sensors were utilized at the V12 growth stage. For all sensors, NDVI and NDRE were calculated. In order to determine VRN, VI data from a plot was divided by that from an N-sufficient reference, generating a sufficiency index value, which then was input in the adapted Holland-Schepers algorithm for sidedress N rate determination. When using NDRE, active sensor had a significantly lower RSNR than passive sensor at multiple PANRs at 4 out of 6 SYs, when passive sensor recommended from 5 to 40 kg/ha more N than the active sensor. When using NDVI, active sensor had a significantly higher RSNR than passive sensor at multiple PANRs at 3 out of 4 SYs, ranging from 2 to 17 kg/ha more N recommended as compared to the passive sensor. VRN generated from passive NDRE was able to accurately approach AONR in 2 out of 6 SYs. Active and passive sensors have the ability to assess N stress and recommend VRN, with passive sensors recommending higher rates more frequently. The use of NDRE from either sensors generated VRN that better approached AONR as compared to NDVI at the V12 growth stage. The determination of N deficiency and sidedress VRN depends on i) the degree of stress at time of sensing as it impacts both the reference value and the remediation extent, and ii) environmental conditions from time of sensing/VRN to harvest.

Keywords. *Multispectral sensor, vegetation index, agronomic optimum nitrogen rate.*

Introduction

Nitrogen (N) is often the most limiting nutrient to plant productivity. In order to maximize yield potential, fertilizer N is supplemented to non-legume crops like corn. Corn fields alone received about 46% of all N applied to crops in 2010 in the U.S. (Economic Research Service, 2013). At the same time that N fertilizer is needed in large quantities, it is also very dynamic and prone to environmental losses once applied to the field. These losses can be significant especially when soil N supply is much greater than the demand by the crop. Furthermore, conditions for both crop N sink and N losses can vary spatially and temporally, with a single rate of N applied to an entire field possibly creating areas of under and over fertilization (Mamo et al., 2003). In order to address these issues, the use of crop canopy sensors for assessing crop N status and applying N variably has been of major research interest.

Both active and passive crop canopy sensors can be used for variable rate N (VRN) management. Recently, many studies have compared how different active crop canopy sensors can be used for VRN (Barker and Sawyer, 2010; Shaver et al., 2011, 2014; Li et al., 2014), but fewer ones have compared active vs. passive sensors (Erdle et al., 2011). Nonetheless, there is a high interest in the potential of data generated by passive sensors since that is the most common type of sensor mounted on unmanned aerial systems (UAS). With the rapidly growing UAS market, there will be an increasing demand for passive sensor data to be used quantitatively in crop-related issues, including N management. Therefore, the objectives of this research were to (i) compare active and passive crop canopy sensors' sidedress variable rate nitrogen (VRN) derived from different vegetation indices (VI) and (ii) assess VRN recommendation accuracy of active and passive sensors as compared to the agronomic optimum N rate (AONR) in irrigated corn.

Material and Methods

This study is comprised of six site-years (SY), conducted in 2015, 2016 and 2017 on different soil types and with a range of preplant-applied N rates (0 to 309 kg N ha^{-1}). The studies were located either on a farmer's field near Central City, NE or at the South Central Agricultural Laboratory (SCAL) near Clay Center, NE. Corn was planted in 76-cm spacing and each plot comprised 4 rows. For all sites, the experiment was a randomized complete-block design with four blocks. Treatment structure was one-way with a control plus four N rates. The N source utilized was either urea-ammonium nitrate or anhydrous ammonia, depending on the SY. Fertilizer N rate was calculated based on the University of Nebraska-Lincoln N recommendation algorithm for corn.

Crop reflectance data was acquired using four different sensors: RapidScan (handheld, active) and Tetracam, MicaSense RedEdge or Parrot Sequoia (unmanned aerial system-mounted, passive). In each SY, a specific passive sensor was utilized (Tetracam for SYs 1,2 and 3, RedEdge for SY 4 and Sequoia for SY 5 and 6), and for all SYs Rapidscan was used as the active sensor. RapidScan CS-45 (Holland Scientific, Lincoln, NE, USA) is an active handheld sensor equipped with a modulated light source and three photodetector measurement channels at 670, 730 and 780 nm. At each crop growth stage sampled, RapidScan was oriented in the nadir position and approximately 0.6 meters above the crop canopy. The two central rows of each plot were scanned individually, producing one average value from each measurement channel per row. RapidScan readings were taken directly over the corn row. Further, values generated for each row were averaged to create one value for each wavelength per plot. The passive multispectral sensors utilized on a given SY were Tetracam MCA6 Mini (Tetracam Inc., Chatsworth, CA, USA), MicaSense RedEdge (MicaSense Inc., Seattle, WA, USA) and Parrot Sequoia (Parrot Inc., San Francisco, CA, USA). Passive sensor-specific information on bands, wavelength center and full width at half maximum (FWHM) are presented on Table 1.

Table 1. Bands, wavelength center and full width at half maximum for each of the sensors used in this study.

	Blue	Green	Red	Red Edge	Near-infrared
	---------------------- Wavelength Center and FWHM (nm) ----------------------				
RapidScan			670	730	780
Tetracam		530 (10)	670 (10)	760 (10)	800 (10)
RedEdge	475 (20)	560 (20)	668 (10)	717 (10)	840 (40)
Sequoia		550 (40)	660 (40)	735 (10)	790 (40)

Each passive sensor was mounted on a UAS, flown to an altitude of 120 m over the plot area and acquired imaging scenes with overlapping regions over the entire study area. A downwelling radiation sensor was mounted on the UAS in order to provide information for radiometric correction. Image radiometric correction was performed on PixelWrench II (Tetracam Inc., Chatsworth, CA) when Tetracam was the passive sensor, and on Atlas (MicaSense Inc., Seattle, WA, USA) and Pix4D (Pix4D S.A., Lausanne, Switzerland) when MicaSense RedEdge and Parrot Sequoia were the passive sensors, respectively. The remaining processing steps were performed on R Statistical Software (R Core Team, 2017). Following image radiometric and geometric adjustment, unsupervised classification and image reclassification were performed in order to distinguish and exclude soil pixels from plant pixels. Thereafter, vegetation indices (VI) were calculated for the entire field and averaged within each plot. NDVI and NDRE were derived from the reflectance data of the red and near-infrared (NIR) bands and red-edge (RE) and NIR bands, respectively.

The treatment receiving the highest N rate in a given SY was considered as the N-sufficient reference in order to calculate a sufficiency index (SI). To calculate an SI, the VI of a treatment was divided by the VI of the N-sufficient reference. Then, the SI was used as an input in the algorithm developed by Holland and Schepers (2010) for sidedress N rate determination. Recommended sidedress N rate (RSNR) was simulated for all treatments using data collected at the V12 corn growth stage. In order to assess sensor and VI performance, RSNR was compared against the agronomic optimal N rate (AONR) for each site. N rate and grain yield information data were fit to linear, linear-plateau, quadratic and quadratic-plateau models. The model with lowest Akaike information criterion was chosen and used to estimate AONR.

The data was analyzed by performing ANOVA on each separate combination of SY and VI. The response variable analyzed was RSNR and explanatory variables in the model were preplant-applied N rate (PANR), sensor type (active vs. passive) and their interaction. Model term significance and pairwise comparisons were performed at alpha=0.05.

Results and Discussion

RSNR response from different sensors varied as a function of SY and PANR. When NDRE was used, RSNR at SY 1 was only affected by PANR, ranging from 120 kg/ha RSNR at 0 kg/ha PANR to 0 kg/ha RSNR at 161 kg N/ha PANR. In SYs 2 through 6, RSNR was affected by sensor type, PANR and their interaction. Active sensor only had a significantly higher RSNR than passive sensor at SY4 at the 0 kg N/ha PANR (Figure 1). Contrastingly, active sensor had a significantly lower RSNR than passive sensor at multiple PANRs at SYs 2, 3, 5 and 6, when passive sensor recommended from 5 to 40 kg/ha more N than the active sensor (Figure 1).

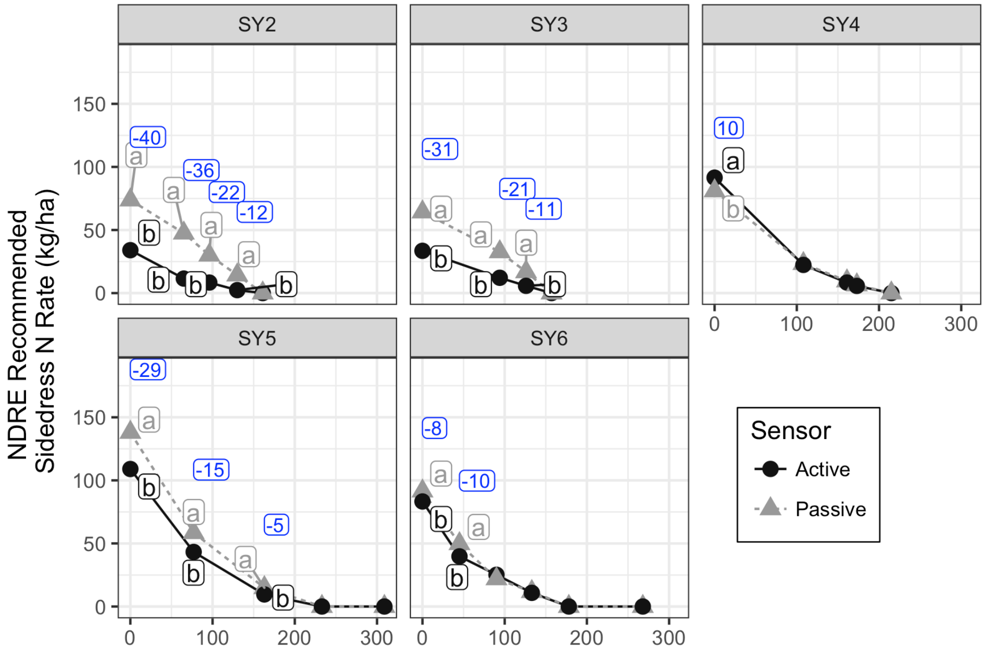

Figure 1. NDRE recommended sidedress N rates from active and passive sensors as a function of preplant-applied N rate (kg/ha) at site-years (SY) 2 through 6. Different letters represent statistically different recommended sidedress N rate between active and passive sensor within a preplant-applied N rate at alpha=0.05. Numbers in blue represent delta recommended sidedress N rate as Active – Passive, in kg/ha.

When NDVI was used, RSNR at SY 1 and 2 were only affected by PANR, and no difference was observed from different sensors. In those cases, RSNR was statistically higher with low PANR (RSNR of 73 kg N/ha at the 0 PANR), and decreased as PANR increased (RSNR of 0 kg N/ha at 161 kg N/ha PANR). RSNR at SY 3 was significantly affected by both sensor type and PANR, with passive sensor recommending 1.6 kg N/ha more than active, and higher RNSR recommended at lower PANRs. On SYs 4, 5 and 6, RSNR derived from NDVI was affected by sensor type, PANR and their interaction (Figure 2). Overall, RSNR was greatest at lower PANR, and decreased as PANR increased in all three SYs for both sensors. Also, active sensor had a consistently higher RSNR than passive sensor at all three SYs when an N deficiency was assessed (Figure 2), ranging from 2 to 17 kg/ha more N recommended as compared to the passive sensor.

Furthermore, regardless of sensor type, NDRE-derived RSNR were consistently greater than NDVI-derived when an N deficiency was observed. This suggests that the red band utilized in NDVI was already saturated and thus less sensitive to different levels of plant N deficiency at the V12 corn growth stage (Gitelson and Merzlyak, 1997).

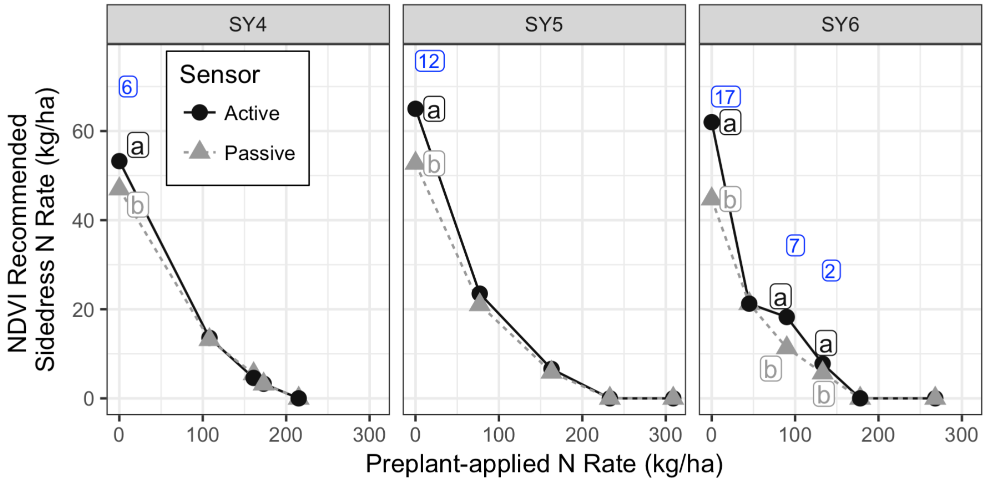

Figure 2. NDVI recommended sidedress N rates from active and passive sensors as a function of preplant-applied N rate (kg/ha) at site-years (SY) 4, 5 and 6. Different letters represent statistically different recommended sidedress N rate between active and passive sensor within a preplant-applied N rate at alpha=0.05. Numbers in blue represent delta recommended sidedress N rate as Active – Passive, in kg/ha.

In order to assess the accuracy of RSNR derived from a given sensor x VI, RSNR was added to the PANR and their total was compared to the SY-specific AONR (Figure 3). On SY1, no sensor by VI combination was able to approach AONR. This was likely due to this SY being over-irrigated by the farmer, which caused even the high N reference to be N deficient. In this situation, a recommendation based on the SI approach would fail since the reference target is below optimum N sufficiency. SYs 2 and 3 presented a low AONR (91 kg N/ha) and showed little responsiveness to N application. Nonetheless, NDRE from passive sensor was better at approaching AONR under lower PANRs as compared to NDRE from active sensor. Also, NDVI from both sensors consistently had a lower RSNR than NDRE. On SY 4, active NDRE was able to better approach AONR at the 0 kg/ha PANR, but performed similarly to passive NDRE at other PANRs. NDRE-based recommendations at this SY were consistently higher and closer to AONR than those based on NDVI. On SYs 5 and 6, no sensor by VI combination was able to approach AONR, in spite of these being N-responsive studies. This situation may arise when N stress is not present at the time of sensing, although it may develop thereafter. In those conditions, sensing and VRN technologies could be more useful if sidedressing N could happen more than once in the growing season.

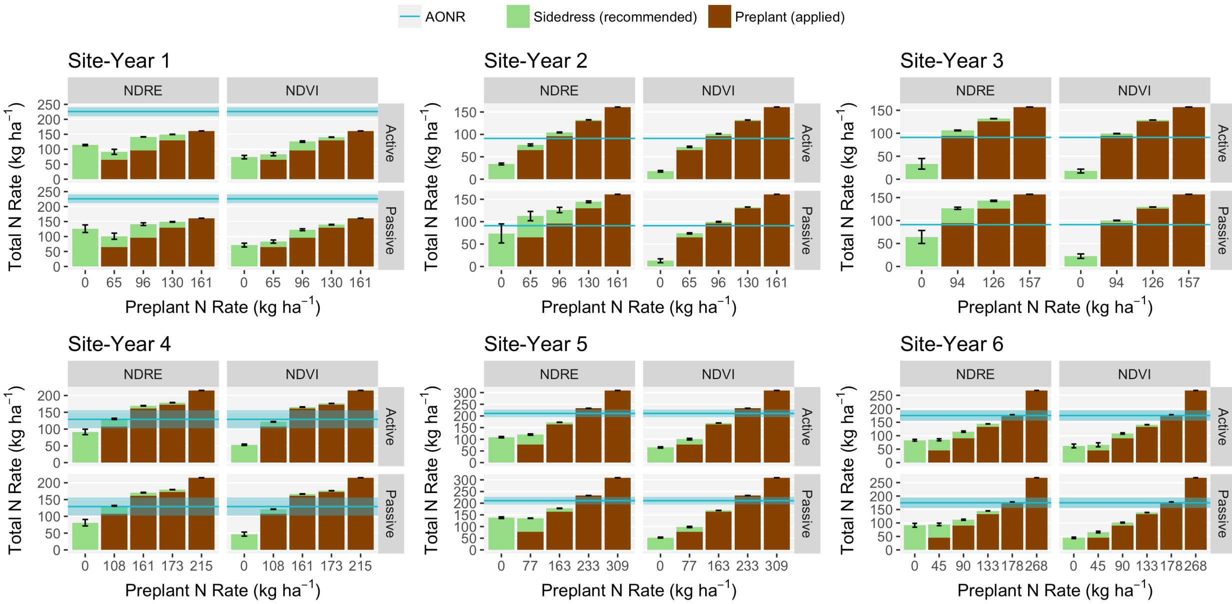

Figure 3. Recommended sidedress N rate (RSNR) calculated using NDRE or NDVI derived from active or passive crop canopy sensor at V12 growth stage for each site-year using the Holland-Schepers algorithm. Black bars represent standard error of the mean of the sidedress variable rate. Light blue horizontal line represents SY-specific AONR, with shaded light blue band representing AONR standard error.

Conclusion

Passive sensor recommended a higher sidedress N rate (5 to 40 kg N/ha more) than active sensor when NDRE was used. In contrast, active sensor recommended a slightly higher sidedress N rate (2 to 17 kg N/ha more) than passive sensor when NDVI was used. Regardless of sensor, overall NDVI-based recommendations were lower than those based on NDRE, suggesting that the use of NDVI in irrigated corn at the V12 growth stage should be cautious due to red band saturation. Most of the SYs in this study did not present a typical yield response to N fertilizer, with SY 1 having all preplant-applied N treatments deficient at time of sensing, SYs 3 showing little N-responsiveness and SYs 5 and 6 likely developing N treatment differences after sensing. With that, only at SY 2 and 4, a specific sensor and VI (i.e. passive NDRE) was able to recommend a sidedress N rate that approached AONR. Active and passive sensors have the ability to assess N stress and recommend VRN, with passive sensors recommending higher rates more frequently. The determination of N deficiency and sidedress VRN depends on i) the degree of stress at time of sensing as it impacts both the reference value and the remediation extent, and ii) environmental conditions from time of sensing/VRN to harvest.

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