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Active and Passive Crop Canopy Sensors as Tools for Nitrogen Management in Corn

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Abstract. *The objectives of this research were to (i) assess the correlation between active and passive crop canopy sensors' vegetation indices at different corn growth stages and (ii) assess sidedress variable rate nitrogen (N) recommendation accuracy of active and passive sensors compared to the agronomic optimum N rate (AONR). The experiment was conducted near Central City, Nebraska on a Novina sandy loam planted to corn on 15 April 2015. The experiment was a randomized complete-block design with four blocks. Treatment structure was one-way with a control plus four N rates (0, 65, 96, 129 and 161 kg N ha^{-1}). The N source for all treatments was urea-ammonium nitrate solution, which was broadcast pre-emergence on 22 April. Crop reflectance data was acquired using two different sensors: RapidScan (handheld, active) and Tetracam (UAS-mounted, passive). RapidScan was utilized to measure crop reflectance at growth stages V9, V13, VT and R4, and Tetracam at V13, VT and R4. For both sensors, NDVI and NDRE were calculated. The treatment receiving the highest N rate (161 kg ha^{-1}) was considered as the N-sufficient reference in order to calculate a sufficiency index, then used as an input in the algorithm for sidedress N rate determination. Passive and active sensor NDRE values were weakly correlated at different crop stages. This was likely the result of the difference in the red-edge band center between the sensors. Nonetheless, NDVI values from passive and active sensors were strongly correlated at crop stages V9 and V13. Using different VIs from either sensor did not produce a sidedress N rate that accurately resembled AONR at any crop stage. However, the AONR value observed for this field may have been biased due to high nitrate leaching conditions, which compromised grain yield response to N fertilizer. Nonetheless, sidedress N rate recommendation derived from both sensors were correlated when NDVI was used at V13. This indicates that both active and UAS-mounted passive sensors have the potential to derive sidedress N rate recommendation in corn at the V13 growth stage. However, caution must be taken to ensure that (i) the correct bands are selected and (ii) the reference area is actually N-sufficient.*

Keywords. *Nitrogen recommendation, unmanned aerial system, reflectance, variable rate.*

Introduction

Nitrogen (N) is often the most limiting nutrient to plant growth and development. Fertilizer N application is a common practice for non-legume high yielding crops, with corn as the major N-consuming crop in the United States. Corn fields alone received 46% of all N fertilizer applied in the U.S. in 2010 (Economic Research Service, 2013). Nitrogen is highly reactive and can undertake different forms in the soil prone to different environmental losses. Due to its reactivity and loss potential, N use efficiency (NUE) by plants is usually low, estimated at 33% worldwide (Raun and Johnson, 1999). A common reason for low observed NUE is the fact that, in many cropping systems, N is applied at a moment when crop N demand is low or even inexistent. Furthermore, besides temporal asynchrony, crop N demand also varies spatially, with the application of a single N rate to an entire field likely promoting over and underfertilized regions (Mamo et al., 2003). To overcome these issues, researchers have been using crop canopy sensors in order to assess and correct in-season crop N deficiency by applying a major portion of the N fertilizer at a time the crop demand is high.

Variable rate (VR) sidedress N management based on crop canopy sensor has been commonly studied with the use of active sensors, such as Greenseeker (GS, NTech Industries, Ukiah, CA) and Crop Circle (CC, Holland Scientific, Lincoln, NE). Many studies have compared the performance of these active sensors to manage N in corn (Barker and Sawyer, 2010; Shaver et al., 2011, 2014; Li et al., 2014). However, very few studies have compared active and passive crop canopy 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.

Active sensors present some key differences compared to passive sensors. For example, active sensors emit their own modulated light and thus sensing conditions are independent of atmospheric conditions, such as cloud cover. Moreover, active sensors have been used “on-the-go”, capable of assessing crop N status and directing VR N application in the same pass. Due to these advantages, commonly used algorithms for VR N recommendation have been developed for active sensors (Holland and Schepers, 2010; Solari et al., 2010).

Passive sensors, on the other hand, may be limited by atmospheric conditions since they rely on sunlight as the energy source. Furthermore, the use of passive sensors to generate VR application is a two-step process, where first the field is imaged, and only after data correction and processing can a prescription map be generated and fed into a VR applicator software. However, UAS-mounted passive sensors have the flexibility of sensing independently of field conditions (e.g. wet soil). Therefore, UAS-mounted passive sensors present a great opportunity for farming management. The literature lacks studies showing its potential for VR N application, especially in comparison to commonly-studied active sensors. Therefore, the objectives of this research were to (i) assess the correlation between active and passive crop canopy sensors’ vegetation indices at different corn growth stages and (ii) assess sidedress VR N recommendation accuracy of active and passive sensors compared to AONR.

Material and Methods

The experiment was conducted on a farmer field (41.275330^{o} N, 97.985439^{o} W) near Central City, NE in 2015. The soil is a Novina sandy loam (coarse-loamy, mixed, superactive, mesic Fluvaquentic Haplustolls). Corn was planted on 15 April in 76-cm rows. Plots were 3 x 20-24 m, comprising four corn rows. Selected soil properties from 0-20 cm depth were 10 g kg^{-1} organic matter, 7.2 pH, 4% clay, 85% sand, 12 ppm P, 104 ppm K, 10.0 ppm NO_3-N and CEC of 7 me 100-g^{-1}. The experiment was a randomized complete-block design with four blocks. Treatment structure was one-way with a control plus four N rates (0, 65, 96, 129 and 161 kg N ha^{-1}). The N source for all treatments was urea-ammonium nitrate (UAN) solution, which was broadcast pre-emergence on 22 April. Fertilizer N rate was calculated based on the University of Nebraska-Lincoln N recommendation algorithm for corn.

Crop reflectance data was acquired using two different sensors: RapidScan (handheld) and Tetracam (UAS-mounted). RapidScan CS-45 (Holland Scientific, Lincoln, NE) is an active handheld sensor equipped with a modulated light source and three photodetector measurement channels at 670, 730 and 780 nm. These wavelengths represent the approximate spectral regions of red, red-edge (RE) and near infrared (NIR), respectively. 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. Before tasseling, RapidScan readings were taken directly over the corn row. At and after tasseling, the readings were taken in the middle of the row in order to avoid the impact the tassel has on reflectance. Further, values generated for each row were averaged to create one value for each wavelength per plot. Tetracam MCA6 Mini is a passive, UAS-mounted sensor equipped with incident light sensor (Tetracam Inc., Chatsworth, CA). Sensor wavelengths are centered at 530, 670, 760, 800 and 970 nm. These wavelengths represent the approximate spectral region of green, red, RE and two NIR bands. At each crop growth stage sampled, the 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. At the time of image acquisition, white 13 x 13 cm tiles were placed outside the plot area, with their location determined by GPS to aid in georeferencing and mosaicking images. 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) and the remaining processing steps were performed on ArcMap (Environmental Systems Research Institute, Redlands, CA). 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. RapidScan was utilized to measure crop reflectance at growth stages V9, V13, VT and R4, and Tetracam at V13, VT and R4. For both sensors, NDVI and NDRE were derived from the reflectance data of the red and NIR bands and RE and NIR bands, respectively.

The treatment receiving the highest N rate (161 kg ha^{-1}) 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.

Sidedress N rate recommendation was simulated for all treatments using data collected at V9 (active sensor only) and V13 (active and passive sensors). In order to assess sensor+algorithm performance, recommended sidedress VR N was compared against the agronomic optimal N rate (AONR) for this site. To calculate AONR, data provided from an adjacent N rate study was used with preplant-applied rates of 0, 45, 90, 135, 179, 224, 269 and 314 kg N ha^{-1}. Using N rate and grain yield information, linear, linear-plateau, quadratic and quadratic-plateau models were fit and the one with lowest Akaike information criterion (AIC) value was chosen.

Results and Discussion

Passive and active sensor NDRE values were weakly correlated at crop stages V13, VT and R4 (r^2 of 0.31, 0.34 and 0.021, respectively, Figure 1). The linear correlation slope for all three crop stages was of small magnitude, 0.06, 0.11 and 0.057 for V13, VT and R4, respectively. Moreover, when sliced by crop stage, most of the variability is found on the active sensor axis (range of 0.17, 0.13 and 0.19 for V13, VT and R4, respectively) and little variability is observed on the passive sensor axis (range of 0.03, 0.03 and 0.07 for V13, VT and R4, respectively). This is likely the result of the difference in wavelength center between sensors, especially for the RE (760 and 730 nm on passive and active sensors, respectively). Although the RE center difference is of only 30 nm between sensors, their reflectance pattern was drastically different, with the passive RE resembling that of the passive NIR band, and the active RE resembling that of the active red band. Shaver et al. (2011) observed no difference in the correlation between NDVI and applied N rate on a study comparing two active sensors with different visible band centers (590 nm on CC and 660 nm on GS), despite reporting a difference in the range readings between the two sensors. However, in that study both band centers were within the visible region of the spectrum, whereas in our study both band centers were within the rapid-changing RE region.

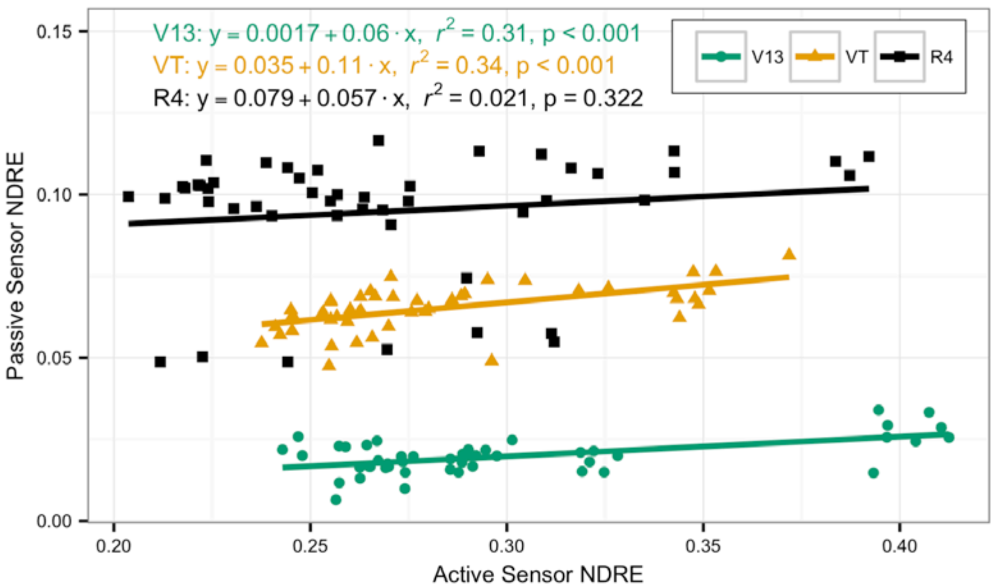

Figure 1 – Passive and active sensor NDRE correlation plot at corn growth stages V13, VT and R4.

Passive and active sensor NDVI values were correlated at crop stages V13, VT and R4 (r^2 of 0.93, 0.83 and 0.85, respectively, Figure 2). The linear correlation slope for V13 and VT was 1.1 and R4 was 0.44. Differences in r^2 observed at different growth stages can be attributed to the decreased sensitiveness of NDVI with increasing crop biomass due to the red band saturation (Gitelson and Merzlyak, 1997). In this case, the saturation effect was more prevalent with the passive sensor than the active sensor as evidenced by their range (0.13 vs. 0.28 for passive and active at R4, respectively). Because NDVI values between sensors were correlated but NDRE values were not, it is likely that discrepancies between sensors may be attributed to differences in wavelength center, especially in the case of the RE band as discussed previously. On a study assessing the correlation of passive and active sensors VI to agronomic parameters in wheat, Erdle et al. (2011) found that different VIs from both types of sensors presented high coefficients of determination when predicting wheat N content, N uptake and N nutrition index at different growth stages over two years. On the same study, authors reported that the best sensor and VI choice across all agronomic parameters was the passive sensor-derived RE_{760}/RE_{730} VI.

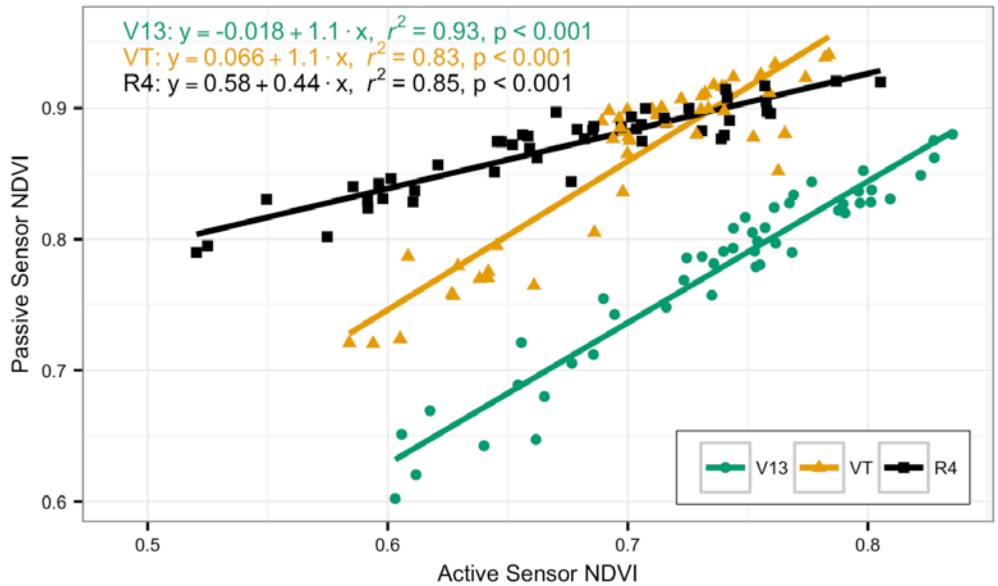

Figure 2 – Passive and active sensor NDVI correlation plot over corn growth stages V13, VT and R4.

The best AIC-based model fit to total N applied vs. grain yield data to determine AONR was the quadratic-plateau (Figure 3a). However, this model produced a negative quadratic term, which is not biologically likely. Due to that, the linear-plateau model was chosen and AONR was determined as 267 kg N ha^{-1} (Figure 3b). Nonetheless, AONR of this site-year should be interpreted with caution due to the fact that the field was subjected to high nitrate losses driven by overirrigation (data not shown), which compromised grain yield response to N fertilizer.

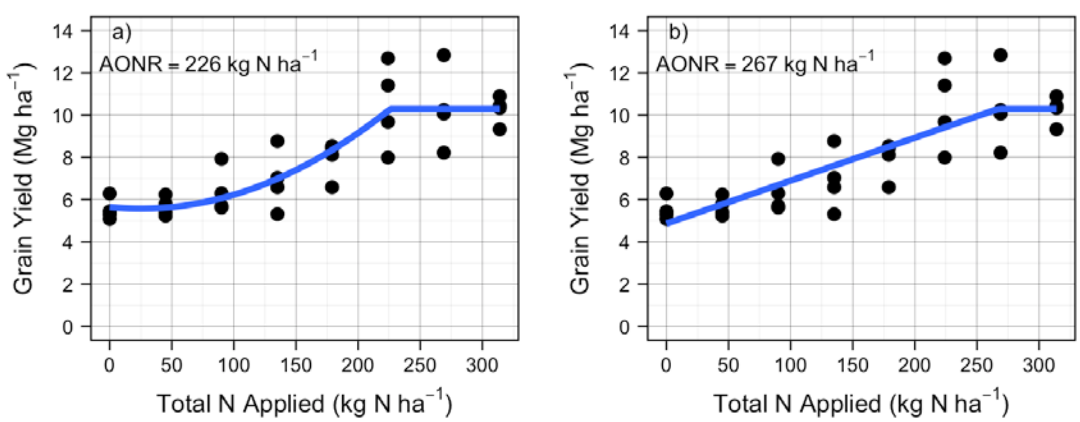

Figure 3 – Grain yield as a function of total N preplant applied fitted with a) quadratic-plateau model and b) linear-plateau model for AONR determination.

At V9, only the active sensor was used to collect crop reflectance data. Sidedress N rate recommendation at V9 using data from the active sensor had similar results across different VIs (Figure 4). Recommended sidedress VR was highest for the 0 N check treatment, as expected, being the closest total N rate to AONR. Sidedress VR N recommendation decreased as preplant N rate increased, with both VIs giving similar results. Similarly, Shaver et al. (2011) observed that NDVI from GS and CC used at V12-V14 were highly correlated to corn response to preplant applied N. Further, the study concluded that both active sensors could be used to address N sidedress application in corn.

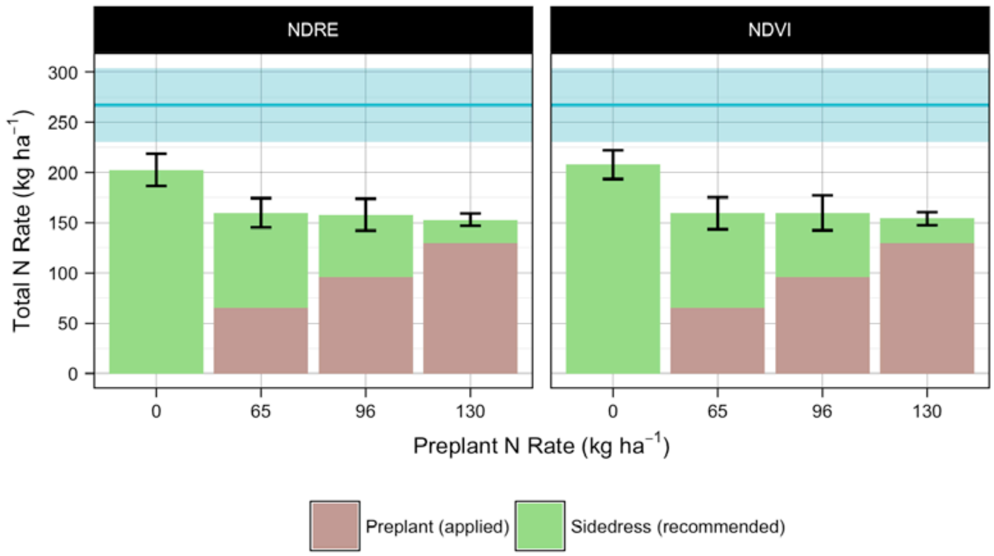

Figure 4 – Sidedress variable N rate recommendation calculated using NDRE or NDVI derived from an active crop canopy sensor used on corn at V9 growth stage. Black bars represent standard error of the mean of the sidedress variable rate. Light blue horizontal line represents AONR (267 kg N ha^{-1}), with shaded light blue band representing AONR standard error.

Sidedress N rate recommendation at V13 using either NDRE or NDVI derived from either the active or passive sensors was significantly lower than AONR (Figure 5). Overall, passive sensor NDRE values had higher variability than those from the active sensor, although the means were comparable except for the 0 N preplant treatment. Passive and active sensor NDVI values were more similar than NDRE, except for the 65 kg N ha^{-1} preplant rate. An issue observed in this study was that, due to excessive N loss through leaching, even the highest N rate could not be considered N-sufficient. In this case, the recommendation for the other N rate treatments was lower than optimal since they were based on a N-deficient reference. This raises a concern for the implementation of sensors to derive sidedress N rate recommendations on a field scale in situations of high N loss. In such a case, the absence of truly N-sufficient areas will cause an underestimation of N sidedress rates.

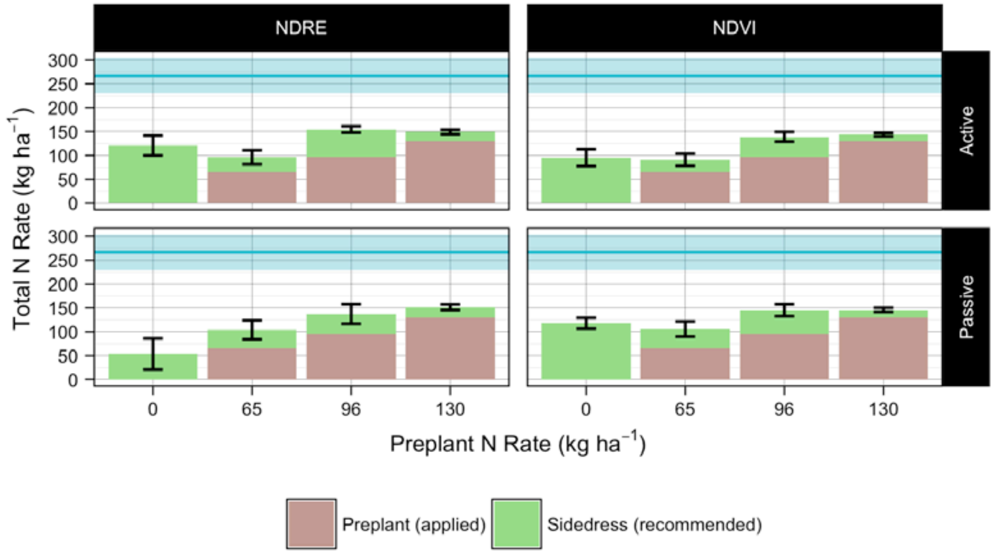

Figure 5 – Sidedress variable N rate recommendation calculated using NDRE or NDVI derived from active or passive crop canopy sensor used on corn at V13 growth stage. Black bars represent standard error of the mean of the sidedress variable rate. Light blue horizontal line represents AONR (267 kg N ha^{-1}), with shaded light blue band representing AONR standard error of the mean.

Correlation between passive and active sensor-derived sidedress N rate recommendation at V13 presented distinct results depending on the vegetation index (Figure 6). When NDRE was used, no linear correlation (r^2=0.517) was observed between the sensors. However, when NDVI was used, a high correlation (r^2=0.85) was observed between the sensors. This result was expected as it followed the same pattern found when regressing passive vs. active NDRE values at V13 (Figure 1). Therefore, NDVI from either passive or active sensor could be used to derive a sidedress N rate recommendation in corn at V13 growth stage.

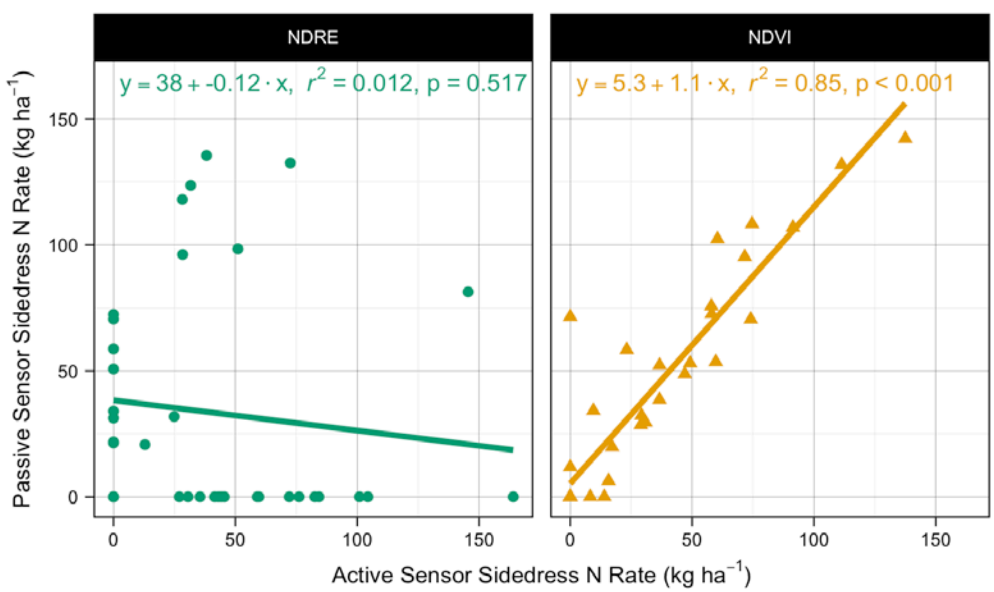

Figure 6 – Correlation plot between active and passive sensors recommended sidedress N rate using NDRE and NDVI at V13 growth stage.

Conclusion

In our study NDRE values from passive and active sensors were weakly correlated at different crop stages. This was the result of the difference in the RE band center between the sensors. However, NDVI values from passive and active sensors were strongly correlated at crop stages V9 and V13. Using different VIs from either sensor did not produce a sidedress N rate that accurately approached AONR at any crop stage. However, the AONR value observed for this field may have been biased due to high nitrate leaching conditions, which compromised grain yield response to N fertilizer. Therefore, comparing sidedress N rate recommendation to AONR in this study should be done with caution. Nonetheless, sidedress N rate recommendation derived from both sensors proved to be correlated when NDVI was used at V13. This indicates that both active and UAS-mounted passive sensors have the potential to derive sidedress N rate recommendation in corn at V13 growth stage. However, caution must be taken to ensure that the correct bands are selected, and the reference area is actually N-sufficient.

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