# Comparing Proximal and Remote Sensors for Variable Rate Nitrogen Management in Cotton

**Anish Bhattarai[1], Amrinder Jakhar[1], Gonzalo Scarpin[1], Leonardo M. Bastos[1]**

[1]University of Georgia, Athens, GA 30602

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## Abstract.

Sensing and variable rate technology are becoming increasingly important in precision agriculture. These technologies utilize sensors to monitor crop growth and health, enabling informed decisions such as diagnosing nitrogen (N) stress and applying variable rates of N. Sensor-based solutions allow for customized N applications based on plant needs and environmental factors. This approach has led to notable reductions in N application rates, minimized N losses by improving N use efficiency (NUE), and increased profitability in cotton production. Previous studies in cotton have shown that using active sensors to determine in-season N rates resulted in reduced N rate (78%), increased NUE (50%), and partial profits (26%), compared to fixed-rate approach. However, active sensors, while insensitive to lighting conditions, face challenges in scalability and require substantial investment. Hence, it is vital to evaluate variable rate N recommendations from different sensing platforms, considering their scalability and cost implications. In this study, we hypothesized that proximal (Crop Circle) and remote sensors (drone-mounted and satellite) as well as different vegetative indices (VIs) and drone image with and without soil generate different N rate recommendations at the time of in-season N application. Therefore, the objectives of this study were to compare the effect of i) three sensor types; ii) two VIs; and iii) two soil-related processing approaches from drone imagery only (removal vs. non-removal of soil pixels) on in-season recommended N rates in cotton. The study was conducted in 2023 in Midville, Georgia, using a randomized complete block design with four replications. The treatment design included three sensors, two VIs, and two processing approaches. The sensor types were hand-held Crop Circle (CC) 435 (Holland-Scientific Inc., Lincoln, NE), drone-mounted MicaSense (MS) Altum-PT (AgEagle, Wichita, KS), and PlanetScope (PS) satellite (Planet, US; 3 x 3 m spatial, daily temporal resolution). The VI types were the normalized difference red edge (NDRE) and the normalized difference vegetative index (NDVI). The processing approaches were to either remove or not remove soil pixels from drone imagery before calculating a N rate. At squaring, CC, MS, and PS were used to sense the variable rate plots. Drone imagery was processed by either removing soil pixels or leaving them in the image. Satellite imagery was obtained within a three-day window of ground sensing and with cloud pixels less than 10%. Sensing data from all three sensors and processing options (for drone imagery only) were used to calculate VIs like NDRE and NDVI. These VIs were then used to calculate in-season N rates using the Holland-Schepers algorithm. Recommended N rates from all three sensors—PS (10 kg N $ha^{-1}$), MS (18 kg N $ha^{-1}$), and CC (20 kg N $ha^{-1}$)—were statistically similar (alpha = 0.05), deviating from our original hypothesis. Similarly, the N recommended rate from two VIs were statistically similar irrespective of the sensor used for sensing ranging from 9 kg N $ha^{-1}$ to 27 kg N $ha^{-1}$ which deviates with our original hypothesis. Moreover, two soil-related processing approaches yielded similar result when the recommended N rate was calculated using NDRE, while they were significantly different when calculated using NDVI.

## Keywords:

Variable rate nitrogen, Drone, satellite, Unmaned aerial vehicle, UAV,sensors.

## 1. Introduction:

In response to the escalating trend in N application and the challenge of spatial and temporal variability, variable rate technology (VRT) emerges as a promising solution. The United States department of agriculture, natural resources conservation service through the environmental quality incentives program, advocates for the use of variable rate nitrogen (VRN) management, offering tailored rates based on soil N and crop needs. Implementing VRN has the potential to address concerns related to nutrient losses such as leaching and runoff (Fabiani et al., 2020).

Precision nitrogen (N) management based on crop reflectance can be used to address over- and under-application of N fertilizer to cotton (Yu et al., 2019). By adjusting application rates, VRT provides greater control over variable inputs, enhancing efficiency without compromising yields (Basso & Antle, 2020). For example, Fabiani et. al. (2020) observed that VRN reduced total N rate in 38% compared to conventional N application while yielding 2.2% more lint yield.

Chua et al. (2003) and Bronson et al. (2006) reported that canopy spectral reflectance has potential to guide in-season N applications in cotton. Sensor-based application is possible as different canopy spectral reflectance can be used to calculate vegetative indices (VI) such as the normalized difference red edge (NDRE). This index is a robust indicator of plant health, particularly chlorophyll content, and correlates highly with crop N requirements (Gitelson et al., 2005). The vegetation index information is then translated to a N fertilizer requirement through an algorithm that modulates the N rate provided by the grower with crop stress information provided by the sensor (K. Holland & Schepers, 2010).

Effective N management is crucial for optimizing crop yield and minimizing environmental impact. Remote sensing technologies play a pivotal role in achieving precision N management by sensing the crop canopy enabling targeted and efficient applications of N, contributing to sustainable agricultural practices (Deng et al., 2018; Tsouros et al., 2019). Sensor-based solutions allow for customized N applications based on plant needs and environmental factors. This approach has led to notable reductions in N application rates, minimized N losses by improving N use efficiency (NUE), and increased profitability in cotton production. VRN of granular fertilizer led to a 39–49% reduction in in-season N inputs and a 30–37% reduction in total N inputs. A 26% improvement in N use efficiency (NUE), and a net return to N cost of €190–248/ha compared to the farmer's uniform application (Stamatiadis et al., 2020). Our previous studies in cotton have shown that using active sensors to determine in-season N rates resulted in reduced N rate (78%), increased NUE (50%), and increased partial profits (26%), when compared to fixed-rate approach.

Satellite- and drone-based remote sensing is increasingly used in agriculture for efficient, sustainable, and profitable crop production (Sishodia et al., 2020). Different sensor types can be used for sensor-based N management in cotton, each with distinct strengths and weaknesses. Proximal sensors, like the Crop Circle (Holland-Scientific Inc., Lincoln, NE), offer highly detailed and real-time data by directly interacting with the crop, providing accurate information on crop health and nutrient status. However, their limited coverage area and dependency on proximity to the target make them less practical for large-scale assessments. Drone-mounted sensors, such as the MicaSense Altum-PT (AgEagle, Wichita, KS), provide versatility and flexibility, covering larger areas with high-resolution imagery and capturing localized variations in soil and crop conditions. Yet, their constrained flight times and weather dependency can impact the frequency and timing of data collection, potentially affecting N management accuracy. Satellite sensors, available through the Planet Data Catalogue (Planet, US; 3 x 3 m spatial, daily temporal resolution), offer broad and consistent coverage over large agricultural regions, enabling insights into macro-level patterns and trends. However, they may lack the fine-scale detail and real-time data needed for precise, time-sensitive N management decisions at the field level. Integrating drone technology with multispectral capabilities shows great potential for improving N management in agriculture by enabling detailed and real-time crop health insights. Additionally, the availability of free and open-source satellite images enhances this study's impact by providing accessible data for N management decisions to anyone, regardless of resources. By using active sensors as the benchmark, this study aims to validate and compare the effectiveness of drones and satellite imagery across various treatments, determining each technology's ability to accurately predict N requirements.

Common approaches for assessing the condition of crops over space and time using these sensors often involve calculating vegetation indices, such as the traditional normalized difference vegetation index (NDVI). Spectral reflectance characteristics of N-deficient plants differ significantly from those of optimally nourished plants at specific wavelengths, making reflectance measurements useful for assessing crop N status in-season. NDVI index is calculated based on normalized red and near-infrared (NIR) spectral bands, influenced by both pigment absorption (in the red) and medium scattering (in the NIR), which is tied to the arrangement of elements in the canopy (structure). Consequently, NDVI is responsive to the greenness of vegetation and the scattering of the canopy, impacting its correlation with crop growth (Plant, 2001). Despite the successes for crop status evaluation using the NDVI calculated from multispectral sensors, it is well documented that NDVI data saturate at high leaf area index values. The NDVI becomes saturated at leaf area index of 3 to 4 for most ecosystems (Sellers et al., 1986) while crop leaf area index often exceeds this value at peak development stages.

The substitution of the red edge for the red spectral band in NDRE enhances its capability to penetrate further into the plant cover, providing valuable insights into the health and conditions of crops. This approach allows for a more comprehensive assessment of crop stress, particularly N stress. In a subsequent study, Rodriguez et al. (2006) observed the potential of NDRE, alongside NDVI, in efficiently detecting N stress in vegetation.

In this study, we hypothesized that proximal sensors (such as Crop Circle) and remote sensors (such as drone-mounted and satellite) generate different N rate recommendations during in-season N application. This hypothesis is based on the differences in sensing height and the varying effects of light, soil, and atmospheric conditions on these sensors. Additionally, we hypothesized that the NDVI and the NDRE produce different N rate recommendations because their differences in the use of spectral bands to calculate the VI, which are then used in the N rate calculation algorithm. Furthermore, we hypothesized that drone images processed with two different approaches—one including soil pixels and one excluding them—yield different N rate recommendations due to the impact of soil as they tend to reduce the overall NDRE and NDVI value.

## 2. Goal and Objectives:

The study aims to assess the accuracy of N rates derived from drone and satellite imagery by comparing them to established ground truth data obtained from active sensors. The objectives include comparing sensor-based recommended N rates with agronomic optimum N rates (AONR), evaluating recommended N rates using various sensors and VIs, and assessing drone-based N recommended rates both with and without considering soil pixels. Through these comparisons, the research aims to provide insights into the effectiveness and reliability of remote sensing techniques in determining optimal N application rates for agricultural purposes.

## 3. Materials and Method:

The research was carried out in 2023 at the Southeast Georgia Research and Education Center in Midville, Georgia (32.86°N, 82.21°W). The field was equipped with pivot irrigation systems. The cotton planting date of the experiment field was on 24th May 2023. N application was done at split with pre-plant application done during the planting and side-dress of N done 45 days after planting on 9th July 2023.

The experimental design was a randomized complete block with four replications. The treatment design on the field included a total of seven treatments including different side-dress N rates ranging from 0 to 128 kg N $ha^{-1}$ and included one sensor-based treatment (Table 1).

Table 1: Nitrogen application rates at preplant and side-dressing of cotton

| N rate (lb $ac^{-1}$) (preplant + side-dressing) | N rate (kg $ha^{-1}$) (preplant + side-dressing) |
|---|---|
| 0 + 0 | 0 + 0 |
| 100 + 0 | 112 + 0 |
| 36 + 24 | 40 + 26 |
| 36 + 54 | 40 + 60 |
| 36 + 84 | 40 + 94 |
| 36 + 114 | 40 + 128 |
| 36 + VRN | 40 + VRN |

The study employed three types of sensors: the hand-held Crop Circle 435 (Holland-Scientific Inc., Lincoln, NE); the drone-mounted MicaSense Altum-PT (AgEagle,Wichita, KS); and the Planet Scope satellite(Planet, CA). Crop circle is equipped with three optical measurement channels, it captures crop-soil reflectance at 670 nm, 730 nm, and 780 nm. It also offers the feature of conducting height-independent spectral reflectance measurements.

Similarly, the Micasense sensor was equipped with five multispectral bands (red: 663–673 nm, green: 550–570 nm, blue: 465–485 nm, red-edge: 712–722 nm, and NIR: 820–860 nm), which was mounted on a drone and deployed. The drone operated with a 75% image overlap, flying autonomously at altitudes up to 51 meters above the ground. This configuration achieved a ground sample distance (GSD) of approximately 0.02 meters. Sensing data collection occurred at the squaring stage of the crop's growth cycle and involved using proximal (Crop Circle) and remote (drone and satellite) sensors on the same day. The handheld active sensor, powered by a small portable battery, was manually moved ~ 0.6 - 0.7 m above the plant canopy on the 5th and 6th rows of each treatment.

In parallel, drone data was collected using a MicaSense Altum-PT multispectral sensor mounted on a DJI Matrice 300 drone. The flight occurred during solar noon, approximately between 12-1 pm, to minimize shadows within or between plant structures. Calibrated reflectance panel images were captured before each flight. The sensor, mounted on the drone, captured images of the research field with an overlapping ratio of 80%. These images were later stitched together using Pix4D mapper (SA, Lausanne, Switzerland), and vegetative indices such as NDRE and NDVI were derived from different bands. Furthermore, Satellite imagery was acquired within a three-day window of the ground sensing activities and with cloud cover below 10%.

The two VIs were evaluated were NDRE and NDVI calculated as follow:

$$\mathrm{NDRE} = \frac{\mathrm{NIR} - \mathrm{RE}}{\mathrm{NIR} + \mathrm{RE}} \quad (1)$$

$$\mathrm{NDVI} = \frac{\mathrm{NIR} - \mathrm{R}}{\mathrm{NIR} + \mathrm{R}} \quad (2)$$

NIR = Near infra-red

RE = Red edge

R = Red

The drone imagery underwent two processing approaches: one involved removing soil pixels before calculating the N rate, while the other retained soil pixels in the imagery. The fine spatial resolution of the drone imagery (0.002 meters) allowed for the clear identification of soil and plant pixels. To evaluate the impact of soil pixels on VRN application, it was necessary to classify the image pixels as either soil or plant. For this classification, a supervised machine learning algorithm called Random Forest was utilized. The training dataset for the algorithm was labeled using the NIR orthomosaic image obtained from Pix4D, processed with the QGIS software. The dataset was divided into a 70/30% train/test split and validated with five-fold cross-validation to ensure robust performance. The difference vegetation index was employed for plant-soil segmentation, as it yielded the best results with an impressive accuracy of 100%. This precise classification was crucial for accurately assessing the effects of soil pixels on VRN decisions, ultimately enhancing the effectiveness of N management strategies.

For the precision management of N within the experimental plots, VRN rates were calculated using the Holland-Schepers equation (K. Holland & Schepers, 2010):

$$\mathrm{Napp} = (\mathrm{EONR} - \mathrm{Ncredits})\ \frac{(1\sqrt[2]{(1-\mathrm{SI})})}{\Delta \mathrm{SI}} \qquad (3)$$

Where,

$N_{app}$ = Recommended N rate

EONR = Economic Optimum N rate

$N_{credits}$ = Pre-applied N

SI = Sufficiency Index

Delta SI = 0.3

The economically optimal nitrogen rate (EONR) was determined based on a yield goal of 1600 lbs. of lint per acre(1795 kg of lint per ha). N credits refer to any N already available to the crop in the soil. In our case, the EONR was reduced by 25% because peanuts, a leguminous crop that contributes N to the soil, were planted in the preceding growing season. Additionally, the rate of pre-plant N application was also subtracted from the EONR.

The sufficiency index (SI) for each VRN plot was calculated using a reference value. This reference value was obtained by extracting the 95th percentile value of the respective vegetation index (VI) for each block using the virtual reference concept (K. H. Holland & Schepers, 2013). Delta SI was fixed at 0.3.

$$\mathrm{SI} = \frac{\mathrm{VI\ sensed}}{\mathrm{VI\ reference}} \qquad (4)$$

To apply N in the research field, a tractor mounted with a boom sprayer specifically designed for this purpose was employed. Attached to the rear of the tractor were 8-row applicators, each equipped with replaceable nozzles of varying sizes. These nozzles facilitated the application of different treatments at variable rates across the field. The tractor's output pressure and speed were calibrated to ensure precise delivery of the designated N rate for each treatment. The N source utilized was urea ammonium nitrate (UAN) 28% N, applied in liquid form at the center of the rows.

Between 170 and 174 days after planting (DAP), the harvesting process was conducted in both fields using a CASE International two-row picker. The third and fourth rows, positioned in the middle of the plot, were picked to provide a representative sample of the entire plot. After harvesting, the seed cotton weight of the collected rows was recorded, and sub-samples were taken for further analysis. The lint and seed obtained from the capsule harvest were then subjected to ginning, a process that separates cotton fibers (lint) from the seeds. The fiber and seeds were weighed separately to determine the ginning turnout percentage. Using this ginning turnout, the total lint yield was calculated for each field's N treatment plots. Cotton lint yield was regressed against total N rate to determine the end-of-season agronomic optimum N rate (AONR) as the optimum point of a quadratic curve describing that relationship. The AONR was used as the benchmark to assess its agreement with that from different sensor, VI, and processing strategies.

## 5. Results:

The total amount of N applied ranged from 0 to 170 kg ha$^{-1}$. Correspondingly, the lint yield varied between 1500 and 2200 kg ha$^{-1}$. The relationship between yield and the total applied N followed a quadratic pattern, as illustrated in Figure 1. Our finding was similar to Sui et. al. (2017) who also found a quadratic relationship of cotton lint yield with the total N rate applied. The agronomic optimum nitrogen rate (AONR) was determined to be 106 kg N ha$^{-1}$. At this optimal N application rate, the lint yield was maximized at 1989 kg ha$^{-1}$. This indicates that applying N at the AONR can effectively enhance lint yield, balancing the benefits of N application against the potential for diminishing returns at higher rates.

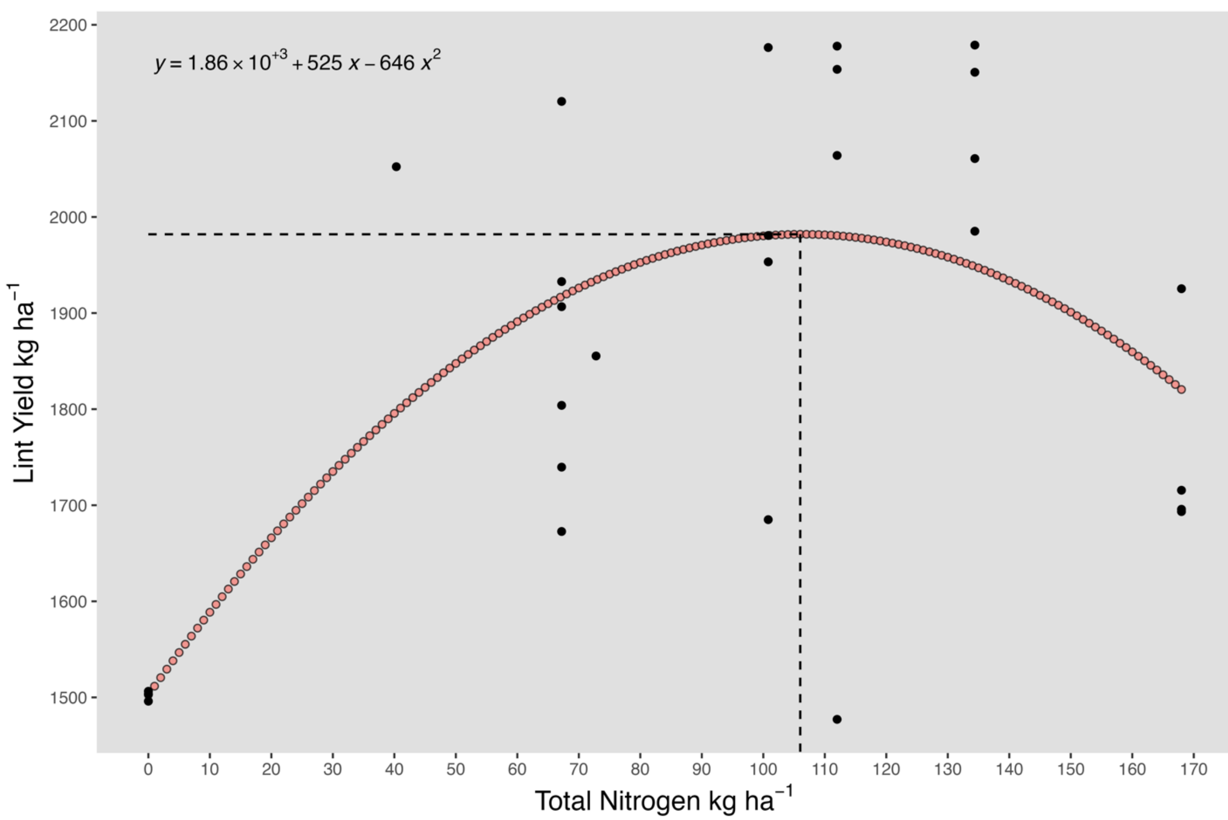


**Figure 1 – Lint yield as a function of total nitrogen applied fitted with the quadratic model for agronomic optimum nitrogen rate determination.**

The AONR was compared with the recommendations generated by four different sensors and two vegetative indices (Figure 2). Among all the combinations, the NDVI and satellite pair recommended the lowest N rate at 49 kg N ha$^{-1}$, which is 54% less than the AONR. In contrast, the NDRE combined with the MicaSense sensor, where soil pixels were retained, recommended a rate closest to the AONR but still 38% lower. In all cases, sensors paired with NDRE provided N rate recommendations that were closer to the AONR compared to those paired with NDVI. This suggests that NDRE-based recommendations are more aligned with the optimal N application needed to maximize lint yield.

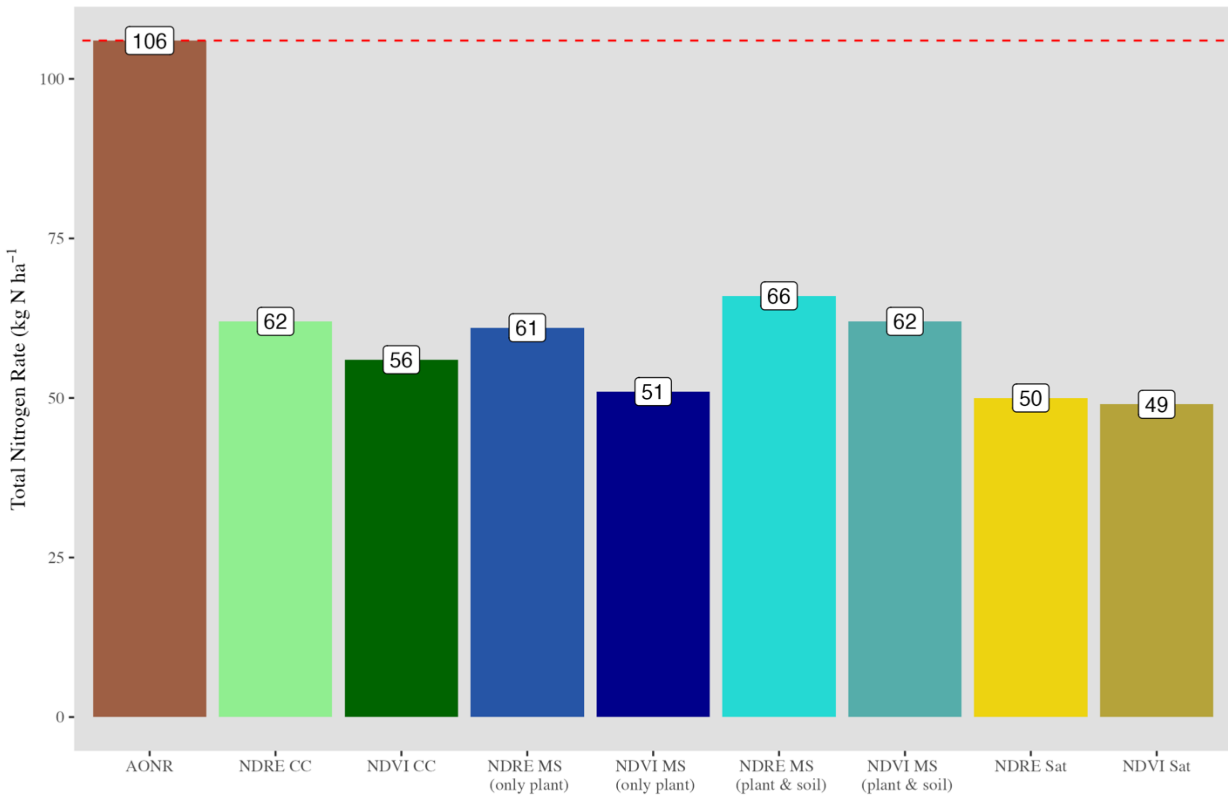


**Figure 2 – dthe combination of four different sensors (cc – Crop Circle, ms – MicaSense, sat – satellite) and two different vegetative indices (NDRE – normalized difference red edge, NDVI – normalized difference vegetative index) with the agronomic optimum nitrogen rate (AONR) for the year 2023. The horizontal red dashed line represents the AONR.**

The mean recommended N rate among four different sensors ranged from 9 kg N ha$^{-1}$ to 30 kg N ha$^{-1}$ when calculated using NDRE with the Holland Schepers' algorithm (Figure 3 left). Similarly, the recommended N rate ranged from 7 kg N ha$^{-1}$ to 25 kg N ha$^{-1}$ when calculated using NDVI with the same algorithm.

When comparing the N rate recommendations for the four sensors using NDRE, Crop Circle, MicaSense (without soil pixels), and PlanetScope satellite were found to be statistically similar. Likewise, the N recommendation rate from the two different approaches of processing the drone images (with and without soil pixels) were also statistically similar.

Among these, the satellite sensor recommended the lowest N rate at 10 kg N ha-$^{1}$, while the MicaSense with both plant and soil pixels recommended the highest rate at 27 kg N ha$^{-1}$.

For the N rate recommendations using NDVI, the Crop Circle, MicaSense (without soil pixels) and the satellite sensor were statistically similar. While the N recommendation rate from two different approaches of processing the drone images (with and without soil pixels) were statistically different. The lower recommendation rate of NDVI + MicaSense (without soil) is likely because of the saturation of red band when only plant pixels were taken into consideration, while the NDRE recommendation of the same sensor was less impacted because the red band is replaced by red edge band, which is more robust against saturation (citation).

The highest N rate was recommended by the MicaSense with plant and soil pixels at 25 kg N ha$^{-1}$, whereas the lowest rate was recommended by the Planet satellite and MicaSense with only plant pixels (Figure 3 right).

These findings indicate that while there is variability among the sensors and indices, the MicaSense sensor, particularly when including both plant and soil pixels, tends to recommend higher N rates, aligning more closely with optimal N application needs of this site and year.

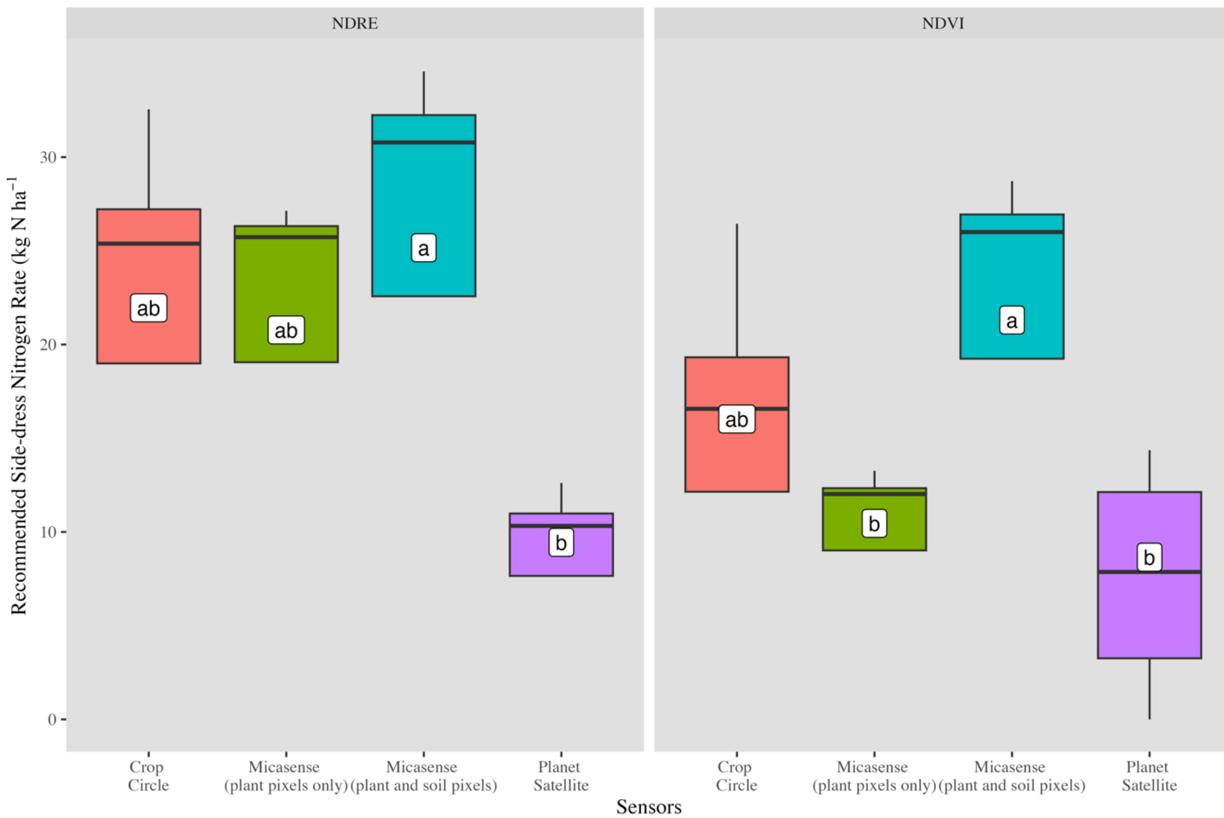


**Figure 3 – Boxplots of recommended side-dress N rate from different sensor-processing combinations in cotton calculated based on two different vegetation indices (normalized difference red edge (NDRE) – left and normalized difference vegetative index (NDVI) – right).**

The mean N recommended rate for NDRE ranged from 9 kg N ha$^{-1}$ to 27 kg N ha$^{-1}$ while for NDVI ranged from 10 kg N ha$^{-1}$ to 20 kg N ha$^{-1}$. The recommended rates from both VI were statistically similar irrespective of the sensor used. This aligns with our hypothesis which suggests that it might be because of the normalization by the reference (sufficiency index) which goes into the algorithm.

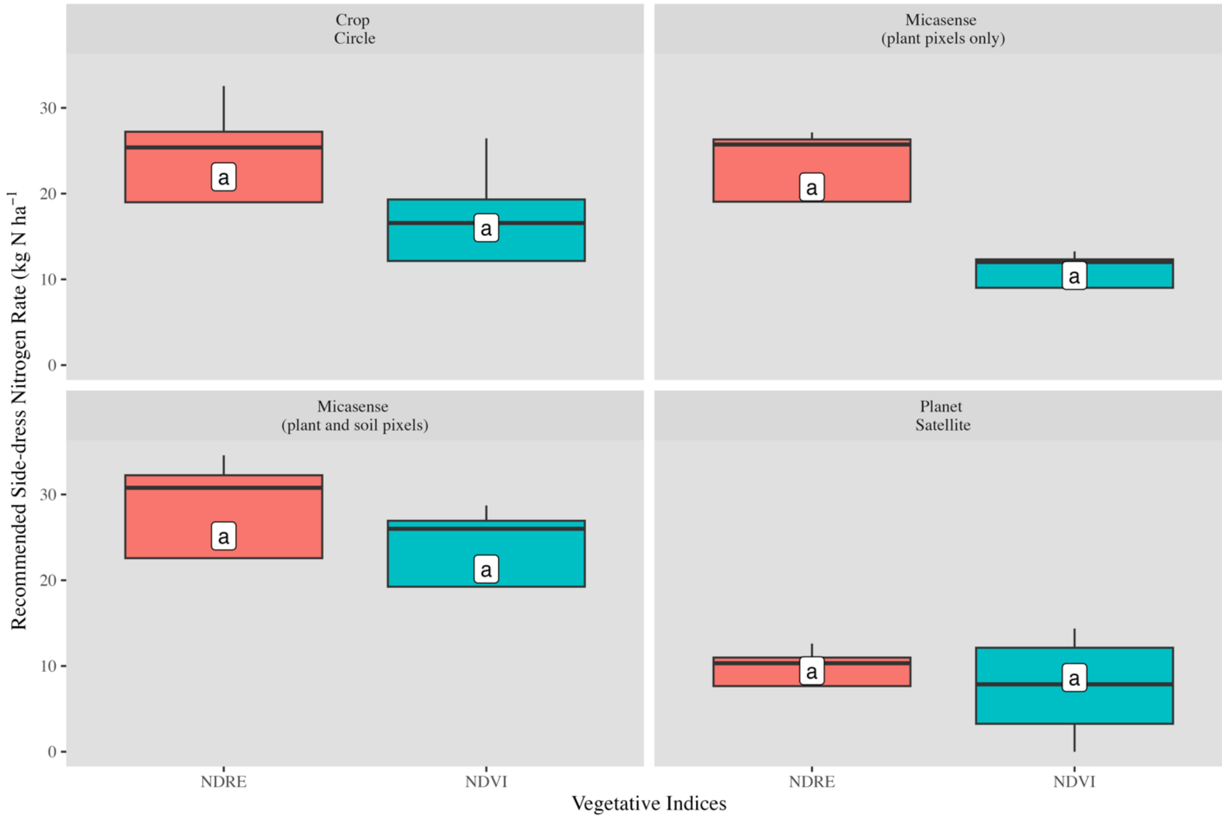


**Figure 4 - Boxplots of the recommended side-dress N rate of different vegetation indices at the time of side-dress application in cotton given by four different sensor-processing combinations**

## 6. Conclusion:

The analysis of N application for cotton lint yield in this study revealed a quadratic relationship, with an AONR of 106 kg N ha$^{-1}$, resulting in a maximum yield of 1989 kg ha$^{-1}$. Comparing different sensors and vegetative indices, it was found that NDRE-based recommendations are closer to the AONR compared to NDVI-based recommendations, indicating better alignment with optimal N needs. Among the sensors, the satellite sensor provided the lowest N rate recommendations, which were statistically similar to other sensors despite the higher spatial resolution. The satellite sensor's ability to offer comparable N recommendations while being free and scalable presents a significant advantage for farmers, making it an efficient tool for optimizing N application in agriculture.

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