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Abstract.

Effective nitrogen (N) management is essential for optimizing corn yield and enhancing agricultural sustainability. Traditional N application methods, typically uniform split pre-plant and in-season applications, often neglect the spatial and temporal variability of N requirements across different fields and years, potentially leading to N overuse. With the rise of precision agriculture technologies, it is crucial to reassess these conventional practices. This study had two main objectives: first, to assess the impact of fixed-rate versus sensor-based variable-rate nitrogen (VRN) applications on corn grain yield, and second, to evaluate how varying pre-plant N rates affect the side-dress VRN prescriptions as determined by different sensors.

This study was conducted in 2023 in Tifton, GA, using a randomized complete block design with four blocks. The treatment design included ten N treatments with varying splits (%) of the total N rate between pre-plant and side-dress rates: 0+0%, 100+0%, 0+100%, (0+VRN), 17+83%, (17+VRN), 25+75%, (25+VRN), and 33+67%, (33+VRN). The total N rate of 336 kg ha^{-1} was based on a yield target of 15,697 kg ha^{-1}.

Nitrogen application recommendations were based on data from three sensors: proximal Crop Circle ACS-435 (Holland Scientific, Lincoln, NE); drone equipped with a Mica Sense Altum-PT (Mica Sense, Seattle, WA, USA); and Planet Scope satellite. Sensor data, collected at the V6 growth stage of corn, involved the normalized difference red-edge vegetation index (NDRE). NDRE values from plots receiving in-season N were compared to that from a N-sufficient reference and utilized in Holland-Schepers algorithm to generate a VRN prescription. Treatments receiving in-season VRN had their rates based on the proximal sensor prescription only.
Sensor-based N management reduced N application rates by 58 kg ha^{-1}, 169 kg ha^{-1}, and 125 kg ha^{-1}, for the 17+83%, 25+75%, and 33+67% treatments, respectively, when compared to the fixed-rate traditional management. The highest yielding treatments were 33+VRN, 25+75, and 17+VRN, ranging from 11,239 to 12,831 kg ha^{-1}. The 0+VRN treatment yielded significantly lower at 6,507 kg ha^{-1}. The control treatment (0+0%) produced the lowest yield (3,106 kg ha^{-1}).

Proximal, drone, and satellite sensors provided similar in-season N recommendations when at least 25% of the total N was applied pre-plant. Without any pre-plant N, significant discrepancies were observed among sensor recommendations: the drone and satellite sensors recommended 66 kg ha^{-1} and 202 kg ha^{-1} more N, respectively, compared to the proximal sensor.

The implementation of sensor-based VRN applications reduced overall N application by 20-60% compared to traditional fixed-rate applications without compromising yield, highlighting precision agriculture's effectiveness in promoting sustainable practices. Consistent recommendations were made by all sensors when at least 25% of N was pre-applied. These results demonstrate sensor-based VRN potential to adapt to specific field conditions and provide accurate N rates, and the feasibility of scaling VRN approaches through satellite technology without compromising recommendation quality.

Keywords.
Variable nitrogen rate, Sensors, Nitrogen, Corn, VRN, Proximal, Drone, Satellite, Active sensor, passive sensor.

Introduction.

Corn (Zea mays L.), a key crop in the United States, is one of the largest consumers of the nation's nitrogen (N) fertilizers. Efficient N management is crucial not only for maximizing crop yields but also for promoting environmental sustainability and profitability in corn farming (Meisinger et al., 2008). Nitrogen is highly reactive, transforming into various forms in the soil that can easily be lost to the environment. This reactivity, combined with often occurring temporal and spatial mismatches in fertilizer application and crop demand, contributes to a globally low N use efficiency (NUE), estimated at only 33% (Raun and Johnson, 1999). Such inefficiencies typically arise from N applications during periods when crop demand is low or absent, and from uniform fertilizer applications that do not account for spatial variability in soil and crop conditions (Mamo et al., 2003).

To address these challenges, precision agriculture technologies have been developed, particularly variable rate N (VRN) management using crop canopy sensors. These technologies adapt N application rates based on real-time assessments of crop health, aligning N rate with crop demands at critical growth stages. Among these technologies, proximal sensors like the Crop Circle ACS-435 (Holland Scientific, Lincoln, NE) have shown significant potential in managing N applications in corn. These sensors, which generate their own light, can operate independently of external light conditions, providing consistent data collection under various atmospheric conditions (Shaver et al., 2011, 2014; Li et al., 2014). However, the dynamic nature of crop N stress and the spatial and temporal variability in N response remain inadequately addressed by traditional fixed-rate fertilization methods (Thompson et al., 2015).

Recent advancements have seen growing interest in drone equipped with passive sensors that rely on sunlight for energy. Although these sensors are subjected to atmospheric conditions that can affect their performance, their ability to provide detailed spatial imaging makes them appealing for VRN applications. Yet, drone deployment involves significant costs, logistical challenges, and is subjected to weather conditions and regulatory constraints. In contrast, satellite imagery offers an alternative with improved affordability, superior temporal resolution and extensive coverage, facilitating consistent crop health monitoring and enhancing VRN management by providing frequent and reliable data.

Given the expanding availability and flexible applications of both drone-mounted passive sensors and satellite technologies, this research aims to bridge the gap in comparative studies that evaluate their effectiveness against the established active sensors in VRN applications. This study has two primary objectives: first, to compare the effects of fixed-rate versus sensor-based VRN applications on corn grain yield; and second, to assess how pre-plant N rates influence the VRN prescriptions generated by different sensor types. By exploring these aspects, this study seeks to identify the potential of different sensor technologies to optimize N application rates, thereby maintaining or enhancing crop yield while decreasing costs in corn production.

Material and Methods.

The study was conducted at Ponder Farm in Tifton, GA (31.50°N, 83.64°W).The soil is also Tifton loamy sand, classified as Fine-loamy, kaolinitic, thermic Plinthic Kandiudults. The experimental design was randomized complete block with four replications. Each plot measured 9.1 x 7.3 m (30 x 24 ft) and included eight crop rows. The total N rate was calculated based on a yield goal of 15,700 kg grain ha^{-1} (250 bu ac^{-1}) and 0.54 kg N per bushel (1.2 lbs N bushel ac^{-1}), resulting in a total N rate of 336 kg N ha^{-1}. This rate was split in different proportions between pre-plant and side-dress across various treatments: 0+0% (no N), 100+0% (full rate at pre-plant only), 0+100% (full rate at side-dress only), 0%+VRN (no N at pre-plant, side-dress rate based on sensor), 17+83% (17% of 336 kg N ha^{-1} at pre-plant, 83% at side-dress), 17%+VRN (17% of 336 kg N ha^{-1} at pre-plant, side-dress rate based on sensor), 25+75%, 25%+VRN, 33+67%, and 33%+VRN.

The Crop Circle ACS-435 sensor (Holland Scientific, Lincoln, NE) was employed to scan the middle two rows of all plots at ~0.7–0.9 m above the canopy when the corn plants reached six fully developed leaves. The sensor path was aligned parallel to the rows, and the beam of light was perpendicular to the row. The ACS-435 sensor, emitting white light, allows for flexible wavelength selection through selectable interference filters. Filters for the wavelengths of green (550 ± 20 nm), red edge (730 ± 10 nm), and NIR (760 nm WLP) bands were selected for this study. Spectral reflectance data were recorded as a text file on an SD flash card using the Holland Scientific Geo SCOUT GLS-400 data logger. The average reflectance values representing each plot were computed from scans of two central rows, with each measurement channel producing one average value per row.

Additionally, a drone equipped with a Mica Sense Altum-PT sensor (AgEagle, Seattle, Washington, USA), featuring five multispectral bands [red (663–673 nm), green (550–570 nm), blue (465–485 nm), red-edge (712–722 nm), NIR (820–860 nm)], was deployed. The drone maintained a 75% image overlap and sidelap, flying under automatic control at altitudes not exceeding 51 m aboveground. This setup resulted in a ground sample distance (GSD) of approximately 0.02 m. Images from the calibration panel were captured before and after each flight to perform the radiometric correction of the images. Images were initially processed in Pix4D (SA, Lausanne, Switzerland), and subsequent orthomosaic processing was conducted in R (version 4.3.1) using the Field Imager Extra package (Pawar & Matias, 2023).

The normalized difference red-edge (NDRE) vegetation index (VI) was used to mask the shadow and soil pixels, with the images segmented into three distinct classes: crop, soil, and shadow. For that, a random forest machine learning approach was employed, using manually labeled NDRE VI data to train the model. The trained model was then applied to classify each pixel into one the three classes of crop, soil, or shadow in all six bands, aligning them with the NDRE VI image using ground control points. In all images, only pixels classified as plant were kept, with remaining classes being masked to NA. Satellite imagery was retrieved within three days prior to the drone flight from the Planet application programming interface. The PlanetScope satellites, part of a constellation comprising over 180 CubeSats with 3U form factors (0.10 m by 0.10 m by 0.30 m), provide global coverage of the land surface with daily updates and a spatial resolution of approximately 3 m across eight spectral bands (blue, green, yellow, red, red-edge, and NIR). The Planet Surface Reflectance product, atmospherically corrected using coefficients from the Planet Analytic Product (Radiance) processed to the surface reflectance, was utilized.

Band data from all three sensors were utilized to calculate NDRE a robust indicator of plant health that correlates with crop N requirements. The VRN rates were determined using the Holland-Schepers equation (Holland & Schepers, 2010). This study also adopted the concept of a virtual reference for N reference plots, as proposed by Holland & Schepers (2013), to calculate a sufficiency index (SI). The SI was computed by dividing the VI of a treatment by the VI of an virtual-reference. Subsequently, the SI served as an input in the algorithm for determining side dress N rates. The prescribed rates derived from the proximal sensor data were then applied to the VRN plots in the field. We also calculated plant coverage by dividing the number of plant pixels in each plot by the total number of plot pixels. The plant pixels were obtained from a prior classification, and the pixel counts were determined using zonal statistics.

Results and Discussion.

Sensor-based VRN application at side-dress varied between 83 and 221 kg N ha^{-1} (Figure 1). This variability resulted in reductions of N application rates ranging from 17% to 50% relative to fixed-rate counterparts. One exception was the scenario without pre-plant N application, where the sensor-based approach applied an additional 160 kg N ha^{-1} at side-dress compared to the fixed-rate approach. Similar results were reported by Bastos (2019) who observed a reduction in 27% of N application rates when utilizing a sensor-based approach. Similarly, Martins et. al (2019) reported a decrease in total N application rates when rates were determined based on crop canopy sensors. These findings underscore the efficacy of VRN technology in reducing N rates compared to traditional practices while at least maintaining yield, thus enhancing N use efficiency. By adjusting N applications in response to real-time crop requirements during critical growth phases, VRN systems not only optimize crop health and yield but also promote environmental sustainability. The targeted N application reduces the risk of excess fertilizer leaching into water bodies and minimizes N runoff, thus contributing to more sustainable agricultural practices and reducing environmental degradation (Wang et al., 2003; Ribaudo et al., 2011).

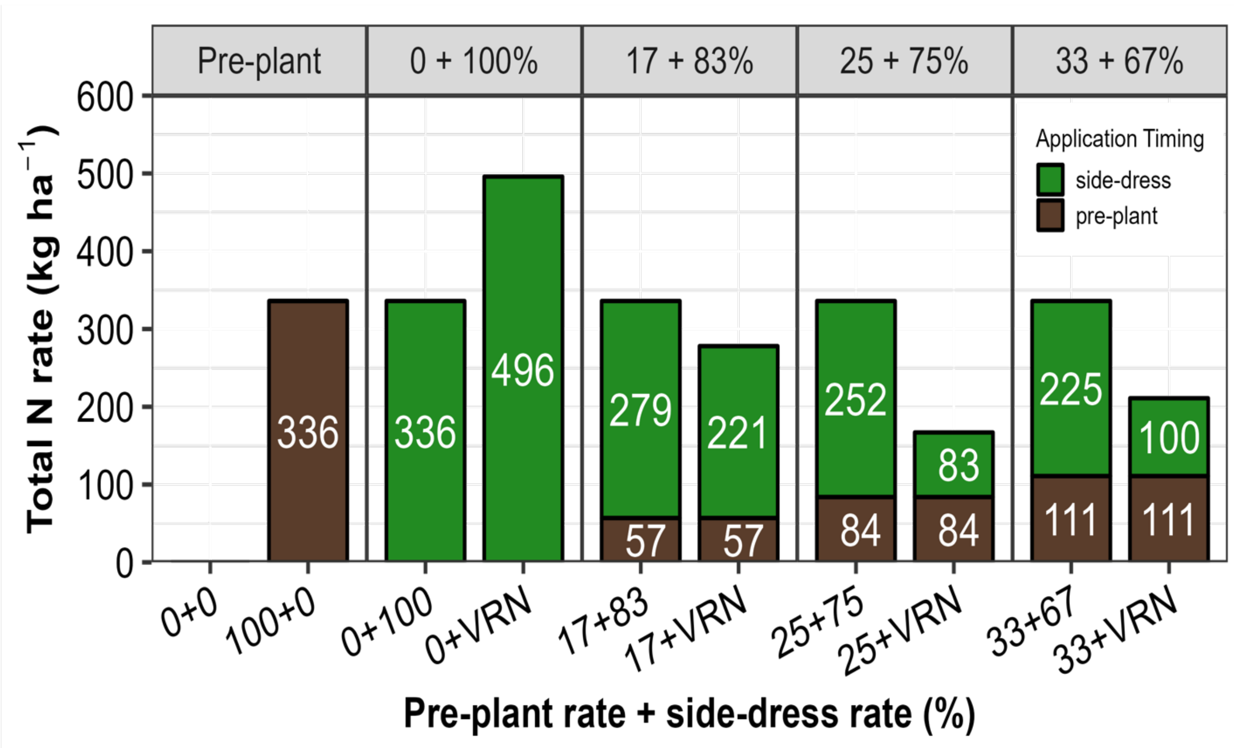

Fig 1. Comparative bar graph of total nitrogen application rates including at pre-plant (brown bars) and side dressing (green bars) for different nitrogen split treatments (VRN = variable rate nitrogen).

Mean yields from N treatments ranged from 3,106 kg grain ha^{-1} in the absence of any N application (0+0) to 12,010 kg grain ha^{-1} achieved with a 33% pre-plant and remainder side-dress application utilizing VRN technology (Figure 2). Yield was optimized when at least 17% of N was applied at pre-plant and regardless of side-dress approach. The highest yield was observed under all treatments that received at least 17% at pre-plant and ranged from 9827 kg ha^{-1} (17+83) to 12010 kg ha^{-1} (33+VRN). This suggests that a balanced approach to N application, particularly one that leverages side-dress applications, can significantly enhance crop yields. Various studies reported similar results where sensor-based approaches were able to reduce N rates in 20-40% compared to traditional fixed-rate without compromising yield levels (Miao et al., 2007; Barker et al., 2017; Martin et al., 2020).

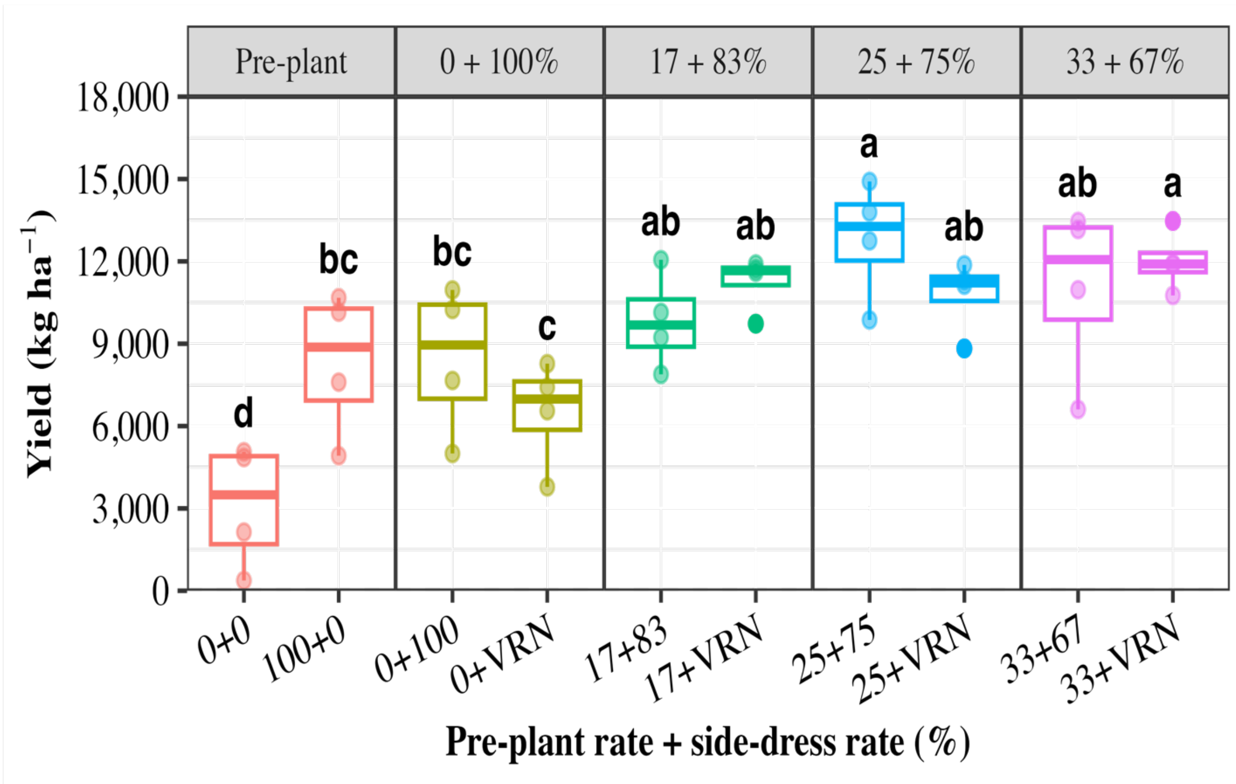

Fig 2. Boxplots of corn yield as influenced by different nitrogen treatments. Boxplots sharing a common letter are not significantly different at alpha = 0.05 (VRN = variable rate nitrogen).

The total N application rates recommended by three different sensors—Proximal (Crop Circle), Drone (MicaSense), and Satellite (Planet Scope)—were evaluated across various N splits. In treatments where 25% and 33% of N was applied as pre-plant, all three sensors recommended similar N rates, demonstrating consistency across sensor technologies under these conditions.However, in scenarios where no N was applied pre-plant or only 17% was applied, the sensors recommended differing N rates. Specifically, drone recommended the highest N rate, followed by the proximal sensor, and the satellite sensor recommended the lowest N rate. This could be attributed to the higher incidence of soil pixels in the satellite images, as indicated in Figure 4. Greater soil reflectance could influence VI values, where darker soils may increase and lighter soils may decrease these values. This interaction highlights the complexity of sensor-based N raterecommendations, emphasizing the need to account for soil characteristics when interpreting remote sensing data for precision agriculture.

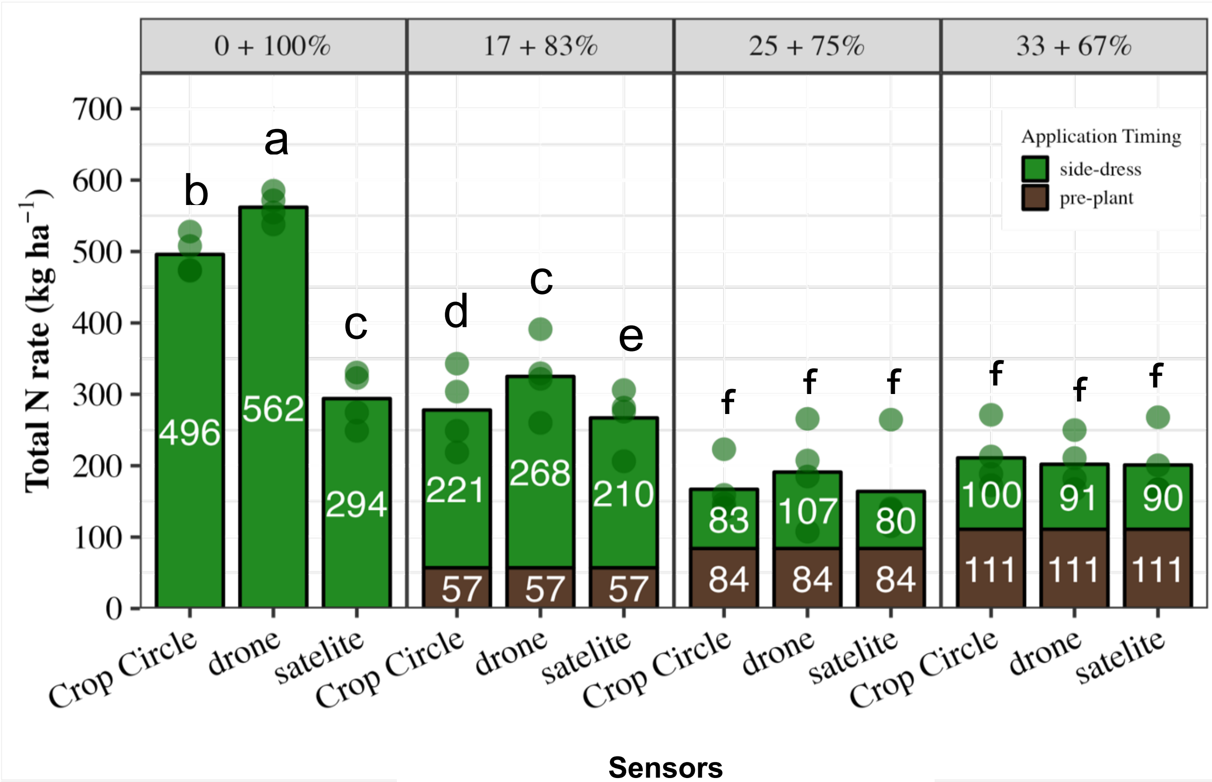

Fig 3. Comparative Bar Graph of Recommended Side-Dress Nitrogen Rates by Proximal, Drone, and Satellite Sensors: Non-Significant Differences Indicated by Identical Letters

Figure 4 illustrates plant coverage across various pre-plant nitrogen (N) application strategies, highlighting the impact of different pre-plant N rates on vegetation coverage. The highest plant coverage was observed on treatments 25+75 and 33+67%, with 62 and 65% of plant coverage . In contrast, for 17+83 and 100+0% treatment the plant coverage was 47 and 40% respectively which was significantly lower than the 25+75 and 33+67% treatment. Notably, the treatment with no pre-plant N application exhibited the lowest plant covergae, which just have 21% of plant coverage, indicating substaplntially less vegetation coverage compared to all other treatments. This data underscores the importance of pre-plant N application in enhancing early plant coverage, which is critical for optimizing growth conditions and potentially influencing subsequent crop yield.

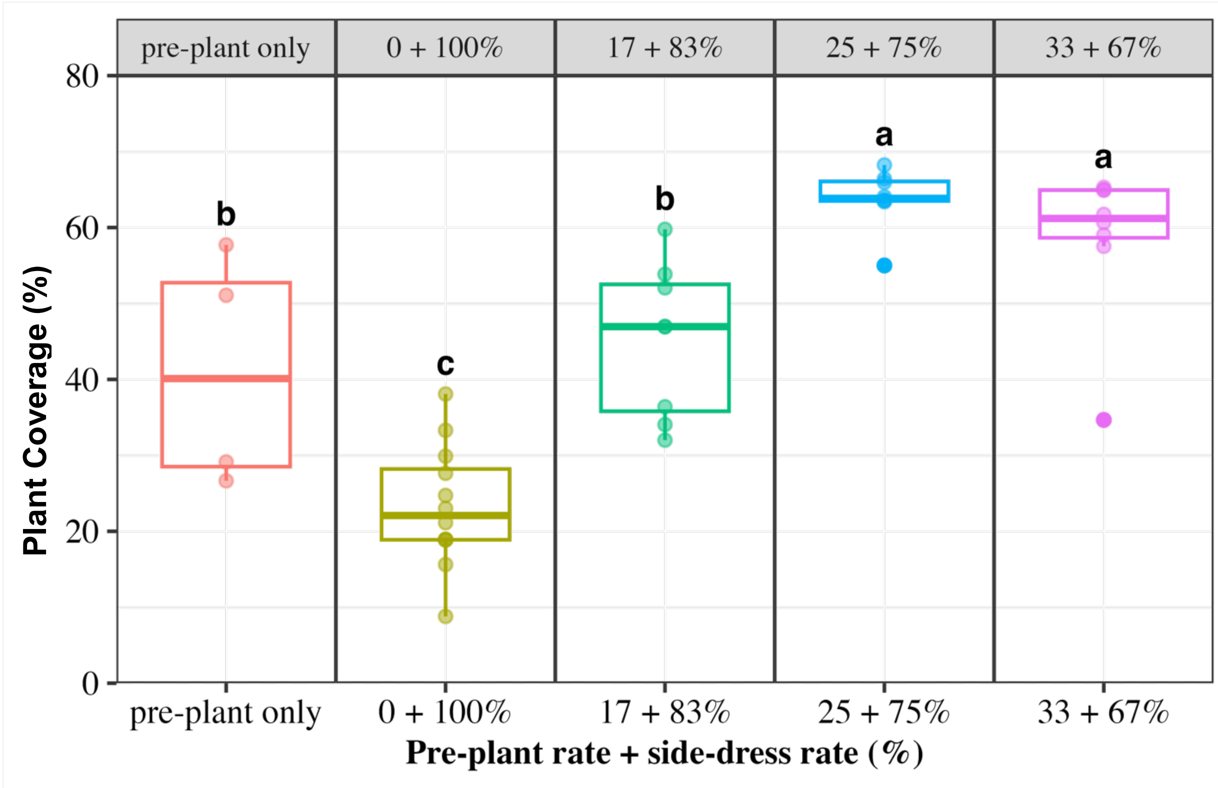

Fig 4. Plant Coverage as Influenced by Different Pre-Plant Nitrogen Application Rates. Coverage areas sharing a common letter are not significantly different at alpha = 0.05.

Conclusion or Summary

Our study demonstrated that yields were consistent across treatments where N application was strategically split between pre-plant and side-dressing phases, affirming the efficacy of sensor-based N management systems in maintaining yields comparable to those of fixed-rate applications. These results underscore the crucial role of split N application strategies in optimizing corn production within Georgia's agricultural context. Additionally, the study highlighted the potential of sensor-based VRN technologies to adapt N applications to specific field conditions, enhancing N use efficiency. The successful integration of satellite technology with VRN approaches suggests that scaling these technologies is feasible without compromising the accuracy of N recommendations. However, caution should be exercised when utilizing different sensors, particularly during the early stages of crop growth or when plant coverage is minimal. Our findings indicate that a minimum of 60% plant coverage is necessary to ensure consistent sensor-based recommendations, pointing to a significant consideration for the effective implementation of VRN strategies in precision agriculture.

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