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Active crop canopy sensors improve nitrogen use efficiency in dryland maize

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Active canopy crop sensor commercialization offers producers the ability to vary nitrogen applications in real time based on crop reflectance measures. However, adoption of active canopy crop sensors has been limited due to inconsistent results, potential yield losses, and lack of information from field-scale trials under different management strategies. Therefore, the purpose of this study was to evaluate the capability of active crop canopy sensor system (OptRx™, Ag Leader, Ames, IA) in field trials on nine non-irrigated maize (Zea mays L.) sites in eastern Nebraska, where rainfall often limits yield (2019–2020). The sensor-based N management treatments were compared to each site's grower treatment, examining the effects of N base rate, in-season application timing, and spatial variability technology performance. The sensor-based N management reduced N application by an average of 38.7 ± 20.8 kg Nha^{-1} without a yield penalty in 77% of the sites (n = 9). The base rate of N applied prior to the in-season, sensor-based application rate in-season, and timing of the in-season application influenced the N use efficiency (NUE) of the sensor-based N management approach. Partial factor productivity of N was improved by 16.8 ± 8.4 kg grain kg N–1 relative to growers' current management. In terms of profit, 35% of sites demonstrated a profit advantage in sensor-based treatments. Field-scale research demonstrates that active canopy sensors can improve nitrogen management efficiency and profitability. These findings highlight the importance of evaluating active canopy crop sensors under variable field conditions to optimize sensor-based N management strategies.

KEYWORDS

nitrogen use efficiency (NUE), partial factor productivity (PFP), nitrogen (N), nitrate (NO3), unmanned aerial vehicle (UAV), normalized difference red edge (NDRE), sufficiency index (SI), estimated nitrogen optimal rate (Nopt)

1 Introduction

While N fertilizer is essential for maintaining high crop production (Mosier et al., 2004), excessive applications can result in negative environmental impact and reduced profits (Schepers et al., 1997; Scharf et al., 2011; Zhang et al., 2015). Determining the optimal N rate is challenging due to the temporal and spatial variation in crop production, N loss, and N mineralization along with the dynamic interactions between soil and water (Mamo et al., 2003; Scharf et al., 2005; Shanahan et al., 2008). This has led to significant interest in site-specific nutrient management to address this spatial and temporal variability (Blackmer and White, 1998; Scharf et al., 2002; Muschietti-Piana et al., 2018; Clark et al., 2020).

With these challenges, the use of technology has the potential to improve nitrogen use efficiency (NUE) and profitability for producers in corn production (Kent Shannon et al., 2018). A variety of prediction methods have been developed across the Midwest to estimate the optimal N rate for a site using management zones and high-resolution data layers in combination with software programs to improve the accuracy of site-specific management (Fleming et al., 2000; Roberts et al., 2012). These methods include yield prediction models (Sibley et al., 2014), maximum return to N calculator (Sawyer et al., 2006), soil sampling (Sawyer and Mallarino, 2017; Morris et al., 2018; Ransom et al., 2020), and N models such as Maize-N (Setiyono et al., 2011) and Adapt-N (Sela et al., 2016). Specifically, Ransom et al. (2020) found that across 31 different corn N recommendation strategies in the Midwest, none of these tools were reliable across the entire region over many years. Thus, highlighting the challenges presented by these methods includes the amount of data required for an accurate recommendation, lack of temporal variability adjustments, averaging of spatial variability, or lack of accuracy for a range of environmental conditions. These challenges are particularly important in rainfed environments, where limited water availability makes the optimal timing and rate of N applications highly dependent on the year's rainfall amount and distribution (Abebe and Feyisa, 2017). Thus, emphasize the importance of prediction models to account for variable environmental conditions, as well as a method to integrate this information with a sensor-based system for improved performance (Clark et al., 2020; Bean et al., 2018a, b; Thompson et al., 2015).

Active crop canopy sensors have been extensively researched since the 1990s for their ability to use real-time reflectance data to guide site-specific N management under variable environmental and seasonal conditions (Blackmer and Schepers, 1995; Bausch and Duke, 1996; Dellinger et al., 2008; Schmidt et al., 2011; Colaço and Bramley, 2018). To account for the spatial variability within a site, these systems use vegetation indices as indicators for N demand for on-the-go variable rate N applications (Raun et al., 2005; Scharf et al., 2002; Shanahan et al., 2008). The GreenSeeker™ Green 506 and Crop Circle™ ACS-210 (Holland Scientific, Lincoln, NE) have been field tested and reviewed with promising results to improve NUE (Barker and Sawyer, 2010; Colaço and Bramley, 2018). Research has focused on not only sensor types but also on refining algorithms behind them, including improving target N rate estimates (Franzen et al., 2016), optimizing application timing (Samborski et al., 2009), and developing response models such as the Holland and Schepers (2010) sufficiency index-based approach. It calculates a sufficiency index (SI) by dividing the vegetation index of the target plants by that of a well-fertilized reference while considering any N credits such as irrigation water nitrates, legume credits, previously applied N, and manure applications. While research algorithm development and calibration are ongoing (Barker and Sawyer, 2010; Whelan et al., 2012; Colaço and Bramley, 2018), accurate field-specific calibration remains essential, especially in rainfed environments where non-N factors such as soil moisture, hybrid differences, disease presence, and environmental conditions are likely to influence accurate SI value. Recent work has incorporated real-time soil and weather data, substantially improving sensor recommendations and alignment with the actual economically optimal nitrogen rate (EONR) (Colaço and Bramley, 2018; Bean et al., 2018b). Thus, reinforcing the need for environmentally responsive algorithms to enhance sensor-based management in water-limited conditions.

Given the variability in field conditions and crop responses, on-farm research has been critical for assessing the accuracy, adaptability, and potential for broader adoption of a sensor-based approach for N management. Early on, Scharf et al. (2011) developed this methodology with a large field-scale study on 55 on-farm research sites where sensor-based N strategies were compared to growers' current N strategies, resulting in an increase in partial profit of \$42 ha^{-1} from both an increase in yield and decrease in N applied in comparison to the producer. Kitchen et al. (2010) elaborated on this concept to evaluate active crop canopy reflectance-based N application compared to growers' current practices to evaluate profitability, resulting in \$25–\$50 per hectare, depending on N fertilizer cost, corn price, and soil type. However, producers are more likely to adopt technology that increases their yield ceiling than technology that may lower their input costs, as most N technologies do (Zhang et al., 2015). Therefore, the improvements of NUE and reduction of environmental impacts of active crop canopy sensors have been well-documented; much less is known about the consistencies in economic returns to the producer (Colaço and Bramley, 2018). Especially in water-limited sites, where the remote sensing techniques raise concerns that water stress may confound nitrogen stress readings (Barnes et al., 2000). In early growth stages, sites with N stress were correlated to many vegetation indices, but in rainfed sites where water is limited, there was little correlation to N stress. Previous studies have noted that these systems need to be tested for separating water stress effects on non-irrigated sites, on-farm applied research instead of simulated results, and understanding spatial variability for evaluating results at a field-length level (Colaço and Bramley, 2018; Samborski et al., 2009; Hatfield et al., 2008).

Therefore, the primary objective of this study was to evaluate the ability of active crop canopy sensors to improve NUE and profitability compared to growers' current N management practices in non-irrigated corn fields in a humid continental climate. Specifically, the OptRx sensor system (Ag Leader Technology, Ames, IA), based on a modified Holland-Schepers model

(Holland and Schepers, 2010), was used to calculate the recommended N target rates from a vegetative index. This approach was applied to examine the impact of in-season application timing, the N base rate, and the difference between the user-estimated optimum N rate and the end-of-season NUE in an active sensor-based system at non-irrigated sites across Nebraska. The secondary objective of this study was to quantify how soil spatial variability, sufficiency index, and rainfall influenced sensor-based management performance. By clarifying the functional role of active canopy crop sensors, this research aims to advance sensor-based approaches to on-farm nitrogen management.

2 Methods

2.1 Research fields

Nine site years (2019–2020) of dryland corn on-farm research experiments were located in eastern Nebraska, USA. Sensor-based N management was evaluated at five sites in 2019 (Sites 1–5) and at four sites in 2020 (Sites 6–9, Figure 1A). Each site was predominantly silt loam and silty clay loam soil types (Table 1). Annual rainfall ranges from 283.5 to 745.7 ml across the sites. The average temperature ranged from −3.31 °C to 31.66 °C throughout the growing season.

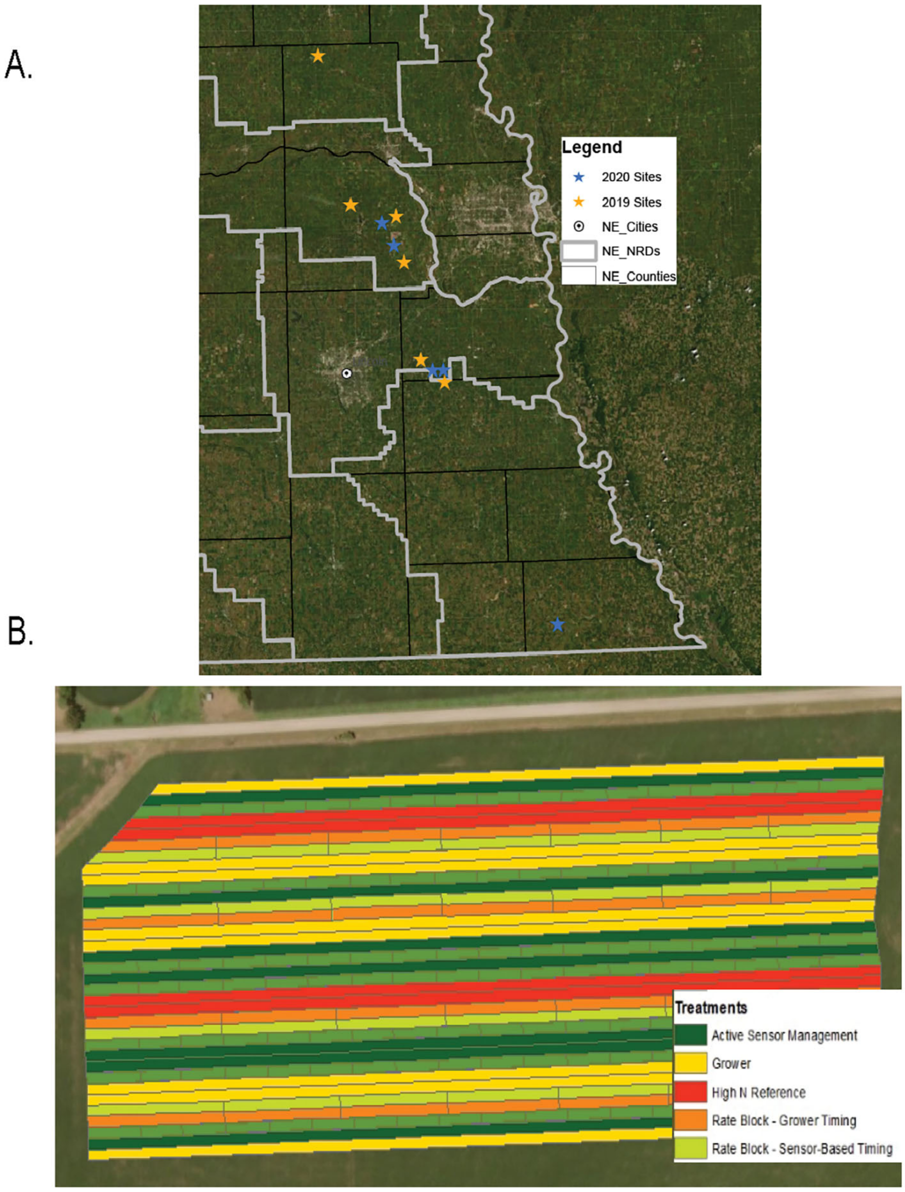

FIGURE 1
Overview of experimental sites and design. **(A)** A map of Nebraska showing all study sites. **(B)** Example of field layout illustrating the experimental design, including nitrogen (N) rate ramp treatments and N reference plots.

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TABLE 1 Site ID, county, year, coordinates, soil type and producer management for all nine experimental sites in eastern Nebraska (USA).

Site id	Year	County	Coordinates	Soil types	Tillage†	Previous crop	Planting date	Hybrid	Seeding rate	Harvest date	Precipitation plant – harvest (mm)	Row spacing (cm)	Reps
									Seeds ha^{-1}				
Site 1	2019	Saunders	41.2624, −96.4799	Yutan, eroded-Judson complex; Yutan, eroded-Aksarben silty clay loam; Nodaway silt loam; Judson silt loam	NT	Soybean	4/20/19	DEKALB DKC63-57	71,661	10/22/19	745.7	76.2	5
Site 2	2019	Saunders	41.1327, −96.4521	Tomek silt loam; Yutan silty clay loam, eroded	NT	Soybean	4/24/19	DEKALB DKC60–88 RIB	69,190	10/31/19	715.1	*	6
Site 3	2019	Dodge	41.7228, −96.7712	Moody silty clay loam; Moody silty clay loam, eroded	NT	Soybean	5/13/19	Fontanelle Hybrids 10D308	79,074	10/24/19	564.1	*	6
Site 4	2019	Saunders	41.2984, −96.6580	Nodaway silt loam; Tomek silt loam; Yutan, eroded, Aksarben silty clay loam	NT	Soybean	5/3/19	Pioneer P1138AM	66,768	11/1/19	712.1	*	6
Site 5	2019	Cass	40.8529, −96.3965	Wymore silty clay loam; Wymore silty clay loam, eroded	NT	Soybean	5/20/19	DEKALB DKC66–75 RIB	68,201	11/8/19	701.4	*	6
Site 6	2020	Saunders	41.1787, −96.4952	Yutan silty clay loam; Tomek silt loam; Filbert silt loam	NT	Soybean	4/23/20	DEKALB® DKC63–57 VTP2 RIB	69,190	10/9/20	283.5	*	5
Site 7	2020	Dodge	41.7352, −96.7881	Moody silty clay loam; Alcester silty clay loam; Coleridge silty clay loam	NT	Soybean	4/30/20	Fontanelle Hybrids® 13D843	76,603	10/9/20	369.8	*	6
Site 8	2020	Cass	40.8304, −96.3687	Wymore silty clay loam; Judson silt loam; Yutan silty clay loam	NT	Soybean	5/2/20	DEKALB® 70–27 RIB	66,718	11/6/20	722.0	*	6
Site 9	2020	Cass	40.8210, −96.3150	Otoe silty clay loam; Wymore silty clay loam	NT	Soybean	5/3/20	Renk RK945DG VT2P RIB	69,190	10/28/20	527.0	*	5

†Number of collared leaves.
‡UAN, urea-ammonium nitrate solution.

TABLE 2 Nutrient management practices include applications, dates, chemical sources, and growth stage at time of application.

Site id	Date	Crop growth stage†	Source‡	N applied (kg N ha $^{-1}$)	Date	Crop growth stage†	Source‡	N applied (kg)	Sensor application date
Site 1	4/17/2019	Pre-plant	Anhydrous ammonia	134.4	–	–	–	–	7/8/2019
Site 2	4/16/2019	Pre-Plant	Anhydrous ammonia	156.8	–	–	–	–	7/3/2019
Site 3	5/13/2019	Planting	32% UAN	39.2	6/13/2019	V8	32% UAN	106.4	7/2/2019
Site 4	5/5/2019	Planting	32% UAN & ATS	42.56	7/3/2019	V8	32% UAN, ATS, Zn, B, Mn		7/3/2019
					7/12/2019	V12	CoRoN®	1.1648	
Site 5	4/1/2019	Pre-plant	11-52-0	36.96	–	–	–	–	7/10/2019
	4/22/2019	Pre-plant	Anhydrous ammonia	197.12	–	–	–	–	
Site 6	3/26/2020	Pre-plant	Anhydrous ammonia	153.44	–	–	–	–	6/17/2020
Site 7	4/30/2020	Planting	32% UAN	39.2	6/17/2020	V9	32% UAN	97.44	6/29/2020
Site 8	4/1/2020	Pre-plant	11-52-0	33.6	–	–	–	–	6/25/2020
	4/4/2020	Pre-plant	Anhydrous ammonia	180.32	–	–	–	–	
Site 9	4/6/2020	Pre-plant	Anhydrous ammonia	196	–	–	–	–	6/25/2020

2.2 Experimental treatments

The factor evaluated was N management strategy with two levels: grower treatment and active sensor-based N treatment. All treatments were replicated six times except for Sites 6, 9, and 1, which contained five replications. The replications were arranged in a randomized complete block design. All prior field management decisions, such as tillage practices, the dates of field operations, hybrid selection, and other management practices, were made by the field owners (Table 1).

The growers' treatment was applied by the site's cooperating producer, and details are presented in Table 2. A base rate of N was applied prior to or at planting to all experimental sites with rates ranging from 33.6 to 156.8 kg N ha^{-1} to establish nitrogen rate blocks (Figure 1B). This allowed for the calculation of EONR after harvest as a metric to benchmark treatment performance. The active sensor treatment consisted of split N applications directed once between V8 and V14 with the appropriate sensor system parameters (see Supplementary Table S1). In the active sensor treatment, a base rate of N was applied at least two weeks prior to the sensor-based N application. This base rate of N ranged between 39.2 and 84.0 kg N ha^{-1} depending on the grower's particular N management program. Base rates of each site were grouped into two categories of "Low," representing base rates between 39 and 45 kg ha^{-1} and the "High" classification, representing rates between 78 and 121 kg ha^{-1}.

Each active sensor treatment N application occurred between the V8 and V12 corn growth stages (Table 3) and was applied using a high-clearance N applicator (DTS-10, Hagie Manufacturing Company, Clarion, IA, USA) with drop tubes. The rate controller consisted of a commercially available system (PinPoint, Capstan Ag, Topeka, KS), with pulse-width modulation (PWM) nozzle solenoid valves to adjust to the changes in target N rate. In 2019, most of the applications occurred near the V12 growth stage, and in 2020, the majority of the applications occurred near the V9 growth stage. The shift to apply earlier in 2020 was made to increase the probability of the site receiving rainfall to incorporate the N application; there is a greater frequency of precipitation approximately one week post application (see Supplementary Table S2), which corresponds to the V9 growth stage (Shulski, 2020). Across all sites, liquid urea ammonium nitrate (UAN) was applied with the high-clearance N applicator for the sensor-based treatments. In 2020, a N pronitridine stabilizer, (Nitrain Bullet™, Loveland Products, Inc., Loveland, CO), was incorporated into the UAN to reduce potential losses to N volatilization.

In this study, active crop canopy sensors (OptRx®, AgLeader, Ames, IA) were used to calculate the vegetative index, Normalized Difference Red Edge (NDRE) (Equation 1):

$$NDRE = \frac{NIR - RE}{NIR + RE} \tag{1}$$

TABLE 3 Site results summary table with comparison between growers' and the active sensor performance for yield, Preplant N, in season Applied N, total N, and partial profit for each field site in 2019 and 2020.

Site	Treatment	Yield (Mg ha^{-1})	Base N (kg ha^{-1})	Sensor applied N (kg ha^{-1})	Total N (kg ha^{-1})	PFP	lbs N bu^{-1}	Partial profit ($ ha^{-1})
Site 1	Grower	15.6	134.4	0.0	134.4	108.0	0.52	343.2
	active sensor	15.1	39.2	85.5	124.7	113.2	0.50	333.1
Site 2	Grower	13.0	156.8	0.0	156.8	77.2	0.73	281.0
	active sensor	12.7	78.4	50.7	129.1	92.3	0.61	278.1
Site 3	Grower	17.6	39.6	0.0	145.6	112.9	0.50	387.3
	active sensor	16.7	39.6	74.0	113.7	136.9	0.41	369.3
Site 4	Grower	11.9	39.6	0.0	138.8	79.9	0.70	230.6
	active sensor	11.9	39.6	98.6	138.2	80.4	0.70	230.7
Site 5	Grower	14.8	154.3	0.0	154.3	89.4	0.63	294.5
	active sensor	14.6	77.5	57.1	134.7	101.0	0.56	290.5
Site 6	Grower	13.9	42.6	0.0	179.2	72.5	0.77	297.7
	active sensor	13.6	42.6	98.6	141.2	90.2	0.62	295.5
Site 7	Grower	13.3	234.1	0.0	234.1	53.0	1.06	279.3
	active sensor	13.4	121.0	61.2	182.2	68.8	0.81	287.6
Site 8	Grower	14.3	213.6	0.0	213.6	62.2	0.90	270.5
	active sensor	12.9	78.7	61.2	139.9	86.0	0.65	254.7
Site 9	Grower	14.2	196.0	0.0	196.0	67.8	0.83	278.1
	active sensor	14.4	78.4	58.7	137.1	97.9	0.57	286.1

where

$$NDRE = Normalized\ Difference\ Red\ Edge$$

$$NIR = NEAR - Infrared\ Wavelength$$

$$RE = Red\ Wedge\ Wavelength$$

and to compute a recommended N rate (Equation 2):

$$N_{APP} = (N_{OPT} - N_{PreFert} - N_{CRD}) \times \frac{\sqrt{(1 - SI)}}{\Delta SI} \quad (2)$$

where

$$N_{APP} = N\ application\ rate$$

$$N_{OPT} = the\ EONR\ or\ the\ maximum\ N\ rate\ prescribed\ by\ producers$$

$$N_{PreFert} = the\ sum\ of\ fertilizer\ N\ applied\ before\ sensor - based\ N\ application.$$

$$N_{CRD} = N\ credit\ for\ previous\ crop,\ NO_3\text{-}in\ irrigation\ water,\ manure\ application,\ etc.$$

$$SI = Sufficiency\ Index\ for\ target\ crop.$$

$$\Delta SI = 1 - S(0);\ the\ difference\ betwteen\ SI = 1\ and\ the\ y - intercept\ of\ the\ N\ response\ curve;\ set\ to\ default\ of\ 0.7$$

The control monitor (Integra, AgLeader, Ames, IA) records NDRE, target N rate, and applied rate in an applied file that was used for treatment implementation control and data analysis.

The OptRx sensor setup requires specific user inputs prior to application. These inputs included corn growth stage, hybrid, estimated N optimum (Nopt), N previously applied, N credits, and the minimum and maximum allowable N rate (Equation 2). The Nopt for each field was determined using a simplified University of Nebraska–Lincoln N algorithm for corn grain without accounting for soil nitrates (Shapiro et al., 2019, Supplementary Table S1). Other Nopt estimation methods were explored on the sites from 2019, including using Maize-N (Setiyono et al., 2011), a simplified UNL algorithm with grower yield goal, the full UNL algorithm (Shapiro et al., 2019), and the simplified UNL algorithm with Hybrid Maize (Yang et al., 2006) to estimate yield goal (Supplementary Table S1).

The yield goal used in these Nopt estimation methods was provided by the producer or calculated from average historical yield data and multiplied by a factor of 1.05 (Dobermann and Shapiro, 2004). The N credits in the sensor system parameters should include any N expected to be applied prior to the sensor application as well as any residual N from previous crops (i.e., soybean). For all sites, that parameter was set at zero to maintain methodological consistency and comparability among sites. As requested by the cooperating producers, the monitor settings for minimum N rate were set at 33.6 kg N ha^{-1} and the maximum N rate was set at 336 kg N ha^{-1}. A sufficiency N strip was placed as a reference for the active sensor treatment. The high-N reference was established at least two weeks prior to the active sensor treatment application to ensure incorporation and N sufficiency, and the NDRE of this area is referred to as the reference NDRE (refNDRE) (Holland and Schepers, 2013). This high-N reference is used to create a sufficiency index (SI) (Equation 3):

$$Sufficiency\ \ Index\ \ (SI) = \frac{NDRE}{refNDRE} \tag{3}$$

where

$$0 \le SI \ \ \ge 1$$

$$NDRE = NDRE\ \ of\ \ target\ \ crop$$

$$refNDRE = NDRE\ \ of\ \ high - N\ \ reference$$

The rate and timing of high-N reference strip establishment and refNDRE at the time of in-season application are included for each site (Table 2).

2.3 Field data collection

2.3.1 Soil data

The coefficient of variation (CoV) in site characteristics, soil electoral conductivity and site elevation were used to assess their influence on site performance between the active sensor-based treatments and the growers' treatments. To do so, soil electrical conductivity data was collected for each site prior to planting using an electromagnetic sensor (DUALEM-21S, Milton, ON, Canada) at 1 m and 2 m depths. Elevation data were collected from the United States Geographical Survey LIDAR dataset at a 1/3 arc-second digital elevation model (DEM) resolution. The slope of each field site' treatment area was calculated from the DEM using the Slope toolbox in ArcGIS (ArcMap v10.6.1, ESRI, Redlands, CA, USA). Site variability in soil electrical conductivity (EC) and elevation was characterized by using coefficient of variance (CoV) (Coefficient of Variation, 2008) (Equation 4) and compared to the CoV of response variables, such as N applied and NUE, to reduce the influence of data point quantity.

$$Coefficient\ \ of\ \ Variation\ \ (CoV) = \frac{\sigma}{\mu} \tag{4}$$

where

$$\sigma = population\ \ standard\ \ deviation$$

$$\mu = population\ \ mean$$

2.3.2 Yield data

Yield data were collected using calibrated yield monitors on the grower's combines and were post-processed using Yield Editor v 2.0.7 (USDA-ARS, Columbia, MO) to adjust for flow delay, moisture delay, maximum and minimum flow velocity, minimum swath width, maximum and minimum yield, overlap at 50% at 0.3-m cell size, and a standard deviation at three standard deviations and five header widths (Sudduth and Drummond, 2007). The harvested weight was manually adjusted for 15.5% grain moisture during post-processing, following established methods (Crowther et al., 2023).

2.4 Data analysis

N as-applied data and clean yield monitor data were spatially joined and averaged within treatment polygons labeled with replications using the analysis toolbox in ArcMap software (Esri, 2019). The results from this analysis were based exclusively on fertilizer-applied nitrogen. For each polygon, the total N applied and yield were used to calculate partial factor productivity (PFP) using Equation 5 (Kalinova et al., 2014):

$$\text{Partial Factor Productivity (PFP)} = \frac{\text{kg grain}}{kg\ N\ fertilizer\ applied} \tag{5}$$

Partial profit was calculated within treatment blocks using yield gain or loss at the price of corn minus the increase or decrease of N applied at the price of N for a particular site (Equation 6, Kitchen et al., 2022). The cost of adopting this technology, including the sensors, machinery, and application equipment, was not included in this partial profit analysis. In 2020, the prices used were \$0.138 U.S.\$ kg corn^{-1}, \$0.904 U.S.\$ kg UAN- N^{-1}, and. \$0.706 U.S.\$ kg anhydrous ammonia- N^{-1}. In 2019, the prices used in the EONR calculation were \$0.151 U.S.\$ kg corn^{-1}, \$0.794 U.S.\$ kg UAN- N^{-1}, and. \$0.706 U.S.\$ kg anhydrous ammonia- N^{-1}. The previous formula is adjusted to each grower's site to accommodate for variations in base rate and the cost of products applied.

$$\begin{aligned}\text{Partial proft} = {} & (\text{Output Quantity (kg corn)} \times \text{Output Price}(U.S.\ kg\ corn^{-1}) - \\ & [(\text{Semsor and or Grower N rate (kg ha}^{-1}) + \text{Base N rate} \\ & (\text{kg ha}^{-1})) \times \text{N Fertilizer Price } (U.S.\ \text{kg N}^{-1})]\end{aligned} \tag{6}$$

To make comparisons between the sites, the inherent yield differences between fields from other management practices or environmental factors were removed by comparing the differences between the growers' treatment and the sensor-based treatment. All reported values for each metric evaluated are the active sensor values minus the growers' values. Overall results comparing treatments and summarized by sites were analyzed using a linear mixed-effects model with a significance level designated at $\rho = 0.05$ unless otherwise stated. Statistics were computed using R (R Core Team, 2020) for running linear mixed-effects models (Bates et al., 2020; Kuznetsova et al., 2017; Lenth, 2021), plotting data

(Kassambara, 2020; Wickham, 2016; Wickham et al., 2020; Hothorn et al., 2021), and processing imagery and spatial files (Bivand, 2020; Bivand and Rundel, 2020; Hijmans, 2020; Pebesma and Bivand, 2021).

Another component of the analysis was to evaluate the influence of soil spatial characteristics on the PFP and partial profit results. To better capture the spatial differences, each treatment strip was divided into smaller 30-m length strips, and each data layer, including the as-applied N data, the yield, soil EC, site elevation, and site slope, was summarized by the mean within each treatment strip. Linear regressions were run to explore the correlation of these site characteristics to the active sensor treatment results.

3 Results

3.1 Active crop canopy sensor management compared to growers' N management

3.1.1 Effect of sensor-based management on rate of N applied, yield, and NUE

To assess the effect of sensor-based management of the rate of N applied, yield, and NUE, the difference in active sensor treatments and grower treatments was compared for applied N and PFP for each site. In all nine of the sites for 2019 and 2020, less N was applied on average with the active sensor treatment than the grower's treatment (Figure 2A). Reduction in N application ranged from 10 to 75 kg N ha^{-1} while on average the reduction in N applied was 38.7 ± 20.8 kg N ha^{-1} (Figure 2A).

The NUE was evaluated using the PFP of the fertilizer applied as calculated in (Equation 5). Even though there were recorded losses in yield, NUE improved on eight of the nine sites with an overall average improvement of 16.8 ± 8.4 kg grain per kg N^{-1} and a maximum improvement of 30 kg grain per kg N^{-1} (Figure 2B).

Since yield is often a critical factor in optimizing profitability and improving NUE, active sensor treatments and grower treatments were also compared for each site. The results show that in seven of the nine sites there were no statistical differences in yield. However, at site 3 and site 8, the yield was significantly reduced by 15.9–22.6 kg ha^{-1} (see Supplementary Figure S1, $\rho < 0.05$). Across all the sites, the average difference between the active sensor treatment and the grower's treatment was −488 ± 689 kg ha^{-1}.

The yield response to N applied was plotted for each site using the means of treatment blocks and randomized static rate blocks. At each site, the average yield resulting from the average N rate applied by the active sensors was then compared to the yield resulting from the sensor rate block of a higher N rate. These two N-rate responses were then also compared for a statistical difference in profitability. In seven of the nine sites, the active sensors' average N rate resulted in the same or greater profit than the profit derived from the next higher rate block, indicating the active sensor treatment likely did not apply enough N to reach EONR (Table 3, $\rho = 0.10$). In the sites where the active sensor's applied rate of N was less than the sensor rate blocks but resulted in a greater yield than those same rate blocks, the difference can be attributed to the active sensors distributing the N rate based on N demand spatially. The proper distribution of N rates was able to increase yield without increasing the overall N applied. Similarly, at sites where the CoV of EC and elevation was greater, the CoV of N applied was also greater. Thus,

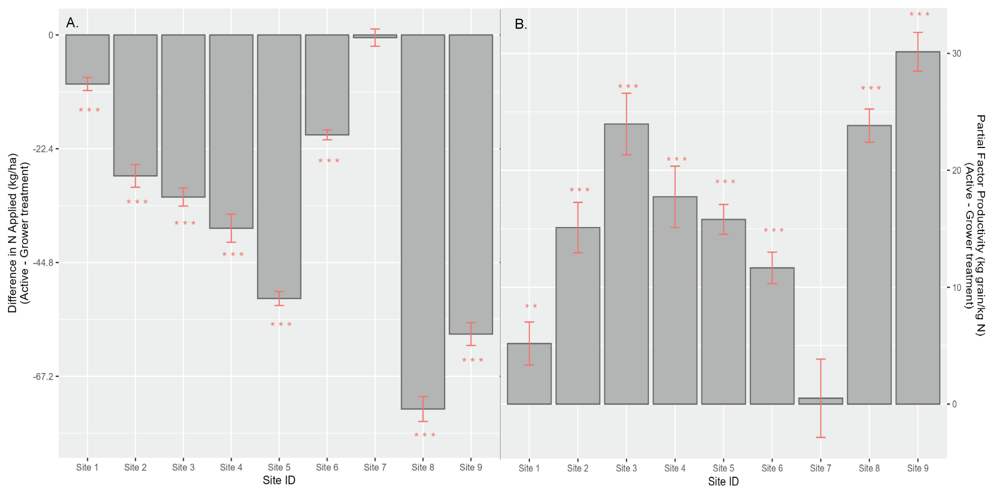

FIGURE 2
N applied and PFP by site. **(A)** The difference in N applied displayed by site and **(B)** the difference in PFP displayed by site **(B)**. Difference is determined by the average active sensor treatment minus the grower treatment. Whiskers represent standard error in the replications. Statistical significance is represented by asterisks above and below the bars (ρ* = 0.1, ρ** = 0.05, and ρ*** = 0.01). Sample sizes (*n*) differ among sites and treatments. All data used for calculating the represented differences can be found in Table 3.

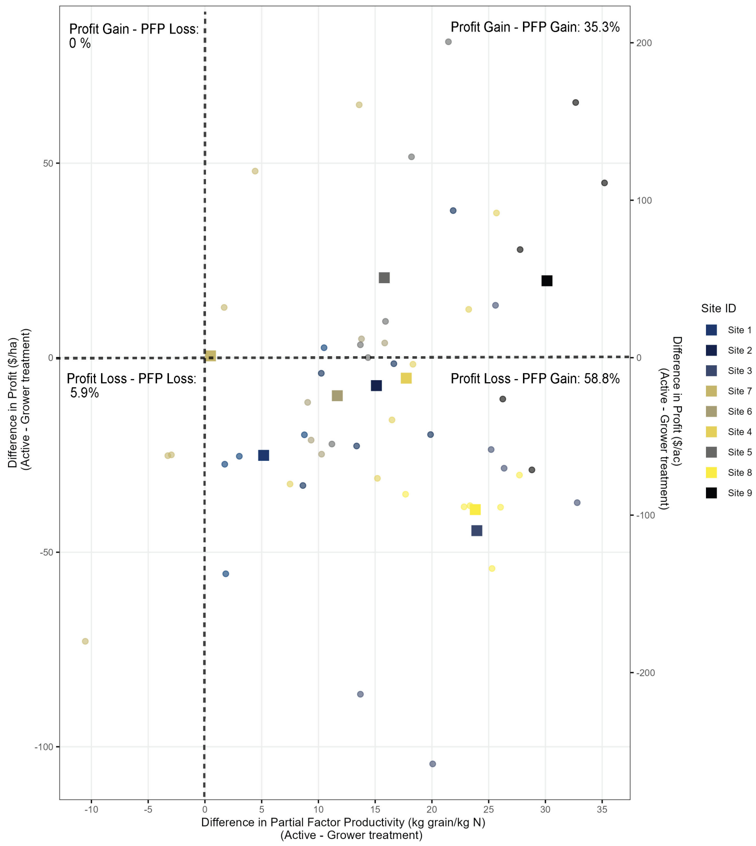

FIGURE 3
Comparison of loss metrics in partial profit and partial factor productivity. Each treatment is represented by Site (squares) and replications (circles) for each site. Loss metrics are calculated as the difference between active sensor treatments and grower treatments in partial profit and partial factor productivity. Each quadrant is separated by dotted black lines and win – loss percentage parameters are placed at the top left of each quadrant. Sample sizes (*n*) differ among sites and treatments.

demonstrating how the active canopy crop sensors responded to variation in crop biomass as reflected by the underlying factor of site and soil variability (Supplementary Figure S3, $R^2 \geq 0.50$; $\rho \leq 0.05$).

3.1.2 Effect of sensor-based management on partial profit

To further analyze the relationship between profit and PFP (kg-grain kg-N^{-1}), the difference between the active sensor treatment and the growers' treatment for each variable was computed to measure loss within each site replicate (Figure 3). Overall, the average difference in profit across all the sites between the active sensor and grower treatment was −$2.40 ± 15.48 US $ ha^{-1} (−$5.93 US $ ac^{-1}). Given this, one-third of the sites were in the top right quadrant, where the active sensor treatment resulted in a greater partial profit and greater NUE than the grower's treatment. The other two-thirds of the sites are in the bottom right quadrant, where the active sensors resulted in greater NUE but a loss in partial profit compared to the grower's treatment. Only one of these sites, SITE 8, resulted in a significant loss of profit from sensor-based treatment (Figure 3, $\rho \leq 0.05$). Last, the left two quadrants display sites where the NUE is lower than the grower's treatment, and although a few replications had this result, no sites resulted in an average loss in NUE.

4 Discussion

The active sensor system applied an average N rate lower than the estimated optimal N rate for the SITE 8 and SITE 9 sites, which may have resulted from underestimated crop N demand (Nopt) at the time of application. Applying the optimal N rate across a field depends on more than an accurate estimate of Nopt; the SI values across the field also contribute to the resulting target N rate. Berntsen et al. (2006) and Colaço and Bramley (2018) described this concept of redistribution of N, where the entire field will average the same amount of N as a uniform flat rate. However, areas of low or high biomass production, depending on the algorithm used, receive less N, and the medium biomass production areas receive more. To explore this redistribution of the Holland-Schepers model (embedded in the OptRx system), the N target rates across each site were compared to the Nopt parameter minus credits for each site. Across all the sites, the average N rate applied was 22.67 kg N ha^{-1} less than the Nopt minus N credits, two values entered into the OptRx^{TM} system. Most N rates within each site were also below this threshold, suggesting that the Nopt and N credit variables used in these studies contributed to lower N rates overall. These results further support why the active sensor treatments consistently applied less N compared to the growers' treatments and indicate that increasing the Nopt value used in the system may be warranted.

Across all sites, sensor-based treatments tended to reduce NUE at high base N sites compared to the growers' current treatment, while sites with low base N showed little change (differences near zero; see Supplementary Figure S2). However, the distribution of NUE differences was not normal (Wilcoxon test, ρ > 0.05), indicating that high base N sites more consistently experience lower NUE under sensor-based treatments than low base sites. To assess the effect of base N rates on the performance of the active sensor system, SITE 6 included a comparison of two base rates (39.2 kg ha^{-1} *vs.* 78.4 kg ha^{-1}) applied at two growth stages (V8 growth stage *vs.* V11 growth stage). The results show an increased distribution of total N rates between the replications at the lower N base rates. This is because the sensor-based system has a greater Nopt-N pre-value (i.e., a greater range of N for the algorithm to operate within) at a lower base rate than a higher base rate. Therefore, SI has a greater influence on the total N applied. Thus, indicating the active sensor system was able to compensate for the difference in base N rates to apply nearly the same amount of total N within the same application timing. A similar result occurred in Thompson and Puntel (2020), where a UAV-based N management had two treatments with the same total N applied following two differing base rates.

Since economic optimum nitrogen rate (EONR) varies throughout a field from varied soil nitrate concentrations, soil characteristics, landscape position, soil-water interactions, and crop N demand (Ransom, 2018; Wang et al., 2020; Crowther et al., 2023). From this, fields of greater spatial variability would have greater variability in EONR values and would benefit from sensor-based variable rate technology. In this study, it was found that the sites with less variability in elevation and soil EC resulted in the greatest differences in N applied and NUE. Further demonstrating how active crop canopy sensors responded to underlying factors like site and soil variability, not just variability in crop biomass. Also suggesting that more homogenous sites (lower CoV) tended to show greater declines in NUE under the evaluated conditions, while more heterogeneous sites displayed more neutral NUE responses. While these results contradict the notion that sites with greater spatial variability would achieve higher NUE, improved NUE —when N rates are at or below EONR—still contributes to reducing potential N losses to the environment (Zhao et al., 2016; Hong et al., 2007). Further research is needed to explore this spatial variability to explain this result.

Overall, the influence from differences in timing, method, or source (i.e., products) of the application between the grower's treatment and the active sensor treatment influenced the yield and partial profit. Particularly in one site, Site 9, where both the grower treatment yield and the yield of the grower rate blocks resulted in a lower yield than the sensor rate block of similar rates. At this site, the grower treatment evidently experienced more N losses from the pre-plant N application timing than the in-season N application with the sensor-based system. These results reflect those of Scharf et al. (2011) and Raun et al. (2005), both of whom observed that sensor-based treatments produced greater yields when their N rate exceeded that of the growers' treatment. In consideration of PFP, three sites, Sites 2, 3, and 8, the grower N rate resulted in a statistically higher partial profit than the rate blocks established during the active sensor application of the same or greater N rate. For example, SITE 8, which experienced rainfall during the growing season, was greater than the 30-year normal precipitation for that field (496.3 > 402.2). Therefore, yields were greater than average. From these results, it can be concluded that other factors, such as N source, differences in N losses, and precipitation, also influenced the yield and partial profit in the treatment comparisons, which is consistent with Spackman et al. (2019). This provides evidence for the importance of understanding the management system surrounding a sensor-based strategy in non-irrigated fields for this technology adoption.

5 Conclusion

The aim of this study was to evaluate the ability of active crop canopy sensors to improve NUE and profitability compared to growers' current N management practices in non-irrigated cornfields in a humid continental climate. In consideration of the impact of in-season application timing, the N base rate, and NUE across all sites, an active sensor-based system applied less N than the growers' current management (38.7 ± 20.8 kg N ha^{-1}). The sensor-based treatment was able to vary the distribution of a similar total N rate according to the crop-specific needs. Accounting for within-field variability improved NUE without yield loss in 77% of the site years, suggesting the sensor-based approach captures spatial in a way that benefits producers. Compared to a fixed N rate applied on the same date and method, sensor-based treatments were more profitable at seven of nine sites, with two sites showing a nonsignificant loss ($2.40 ± 15.48 U.S. $ ha^{-1}). Other factors such as rainfall following application, average SI at the time of application, and soil variability did not have a direct correlation to the profitability of sensor-based technology. Therefore, these results demonstrate the application timing, source, and method all greatly influence the N response, especially in non-irrigated silt loam soils of eastern Nebraska.

While N fertilizer remains a critical crop input, determining the optimal N rate is further complicated by the spatial and temporal variability in non-irrigated maize production (Mosier et al., 2004; Scharf et al., 2011; Zhang et al., 2015). Variability that drives differences in field conditions and crop responses highlights the importance of on-farm research to critically evaluate the broad-scale adoption of sensor-based approaches for N management in maize production. Overall, as site variability increased, as characterized by the coefficient of variation of soil EC and site elevation, the variation of N applied using the sensor-based system also increased. However, the insights from this study show the active sensor systems were able to compensate for the differences in base N rates to apply nearly the same amount of total N within the same application timing. Continued efforts are needed to improve the understanding of how the conditions under which sensor-based N management is most effective to support broader on-farm adoption.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Author contributions

SK: Investigation, Formal Analysis, Project administration, Data curation, Visualization, Writing – original draft, Conceptualization, Writing – review & editing, Methodology. KB: Visualization, Writing – review & editing. JL: Supervision, Writing – review & editing, Resources, Methodology, Validation, Funding acquisition, Project administration. LP: Writing – review & editing, Investigation, Methodology, Supervision. LT: Investigation, Supervision, Writing – review & editing, Methodology. GB: Writing – review & editing.

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Conflict of interest

The author(s) declared that this work was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Supplementary material

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fagro.2025.1722488/full#supplementary-material

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