On-farm Evaluation of a Remote Sensing-based Precision Nitrogen Management Strategy

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Abstract.
Remote sensing and the Ramp Calibration Strips (RCS) have been proposed to optimize crop nitrogen (N) management. However, weather uncertainty during the reproductive period and within-field variability of other factors could cause mismatches between in-season vegetation index responses and final yield responses to N. The evaluation of the potential of RCS_based precision N management (PNM) strategy across a wide range of soil and weather environments is necessary. This study aimed to validate and evaluate the potential of this RCS-based PNM strategy to determine site-specific maximum return to N (MRTN) rates for corn around V8-V9 growth stages across the US Midwest Corn Belt. Data from 49 site-years of N rate experiments across eight states in the US Midwest were analyzed. The study compared the RCS-based strategy with traditional farmer N practices. The results showed significant variability in state-specific MRTN rates, with Missouri having the highest mean MRTN following soybean and North Dakota having the lowest mean MRTN following soybean and sunflower. The coefficient of variation (CV) values highlighted the substantial within-state site-specific MRTN variability. The RCS-based strategy using normalized difference vegetation index (NDVI) and normalized difference red edge (NDRE) obtained with an active canopy sensor RapidSCAN achieved moderate accuracy in estimating site-specific MRTN (R^2=0.44–0.48), with NDRE performing slightly better. Both vegetation index-based strategies outperformed farmer N practices, showing lower root mean squared error (RMSE) values (no more than 50 kg N ha^{-1}) and higher percentages (65–78%) of 'Good' sites, indicating more accurate MRTN estimates. Further research is needed to assess its effectiveness under more diverse on-farm conditions.

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Precision nitrogen management, Ramp Calibration Strip, maximum return to nitrogen, NDVI, NDRE, US Midwest Corn Belt.

Introduction

Traditional nitrogen (N) fertilizer management relies on farmer's empirical knowledge of yield responses to N, typically applying a uniform N rate across the entire field and years(Miao et al. 2011). However, such management might often suffer when dealing with the dynamic needs of crops, the heterogeneity within fields, and year-to-year weather differences. In contrast, precision N management (PNM) incorporates an array of advanced technologies and methods to optimize N supply based on crop demand (Miao et al. 2011; Ransom et al. 2020). One key aspect of PNM is the use of remote sensing technology, which allows for real-time monitoring of crop N deficiency and growth, enabling farmers to apply N precisely where and when it is needed (Lu et al. 2022). Additionally, soil sensor testing provides valuable insights into fertility levels and soil composition, guiding the application of N for optimal performances (Liu et al. 2023). Moreover, yield map-based zone management could help to identify areas within fields that have distinct productive patterns, allowing for tailored N application based on specific needs (Miao et al. 2018). Crop models further contribute to PNM by simulating various nitrogen application scenarios, helping farmers make informed decisions to maximize economic returns and minimize environmental impact (Miao et al. 2006). By balancing N supply with crop demand using these technologies, PNM aims to enhance N use efficiency (NUE), increase crop yields, and mitigate the environmental risks associated with reactive N pollution, which contributes to sustainable agriculture practices (Miao et al. 2011).

Multiple N recommendation strategies in PNM have been reported to perform better compared to conventional farmer management practices. To facilitate rapid and widespread application under various production conditions, some scholars have evaluated various N recommendation strategies through plot experiments, on-farm trials, and regional model scales. However, due to diverse growing environments and limitations of different strategies, no single N recommendation tool was universally reliable (Ransom et al. 2020). There remains a need to develop or optimize N recommendation strategies that accommodate the diversity of soils and weather conditions and are closely aligned with local crop varieties.

The Ramp Calibration Strip (RCS) strategy was proposed as a practical PNM method (Raun et al., 2008). By implementing RCS and utilizing proximal remote sensing technologies, it is possible to monitor the seasonal and spatial dynamics of N at each crop growth stage, thereby estimating the optimum N rates (such as agronomic optimal N rate (AONR), economic optimal N rate (EONR), and maximum return to N (MRTN)) within a field during the growing season. The RCS-based N recommendation can estimate N requirements without the need to independently determine each component of the N cycle (such as mineralization, leaching, and denitrification). However, weather uncertainty during the reproductive period and other factors contributing to within-field variability can still cause a mismatch between in-season vegetation index responses to N and final yield responses to N. Therefore, more research is needed to evaluate and improve this strategy across a wide range of soil and weather environments.

This study aimed to evaluate and improve the RCS-based precision N management strategy to determine site-specific MRTN for corn around V8-V9 growth stages using remote sensing technology in the US Midwest Corn Belt.

Materials and methods

Study site description and experiment design

The database in this study included information about different soil types, weather conditions, and typical management practices. It came from a research collaboration between Corteva Agrisciences and eight universities in the US Midwest, covering 49 site-years across Iowa, Illinois, Indiana, Minnesota, Missouri, North Dakota, Nebraska, and Wisconsin from 2014 to 2016. Each state conducted calibration plot experiments on two sites in each year, with Missouri adding a third site in 2016. About half of the sites were located on farmers' fields, while the rest were on university research stations. Each site involved the treatments applying ammonium nitrate fertilizer at rates ranging from 0 to 315 kg N ha^{-1} in 45 kg N ha^{-1} increments. These applications were either entirely at planting or split, with 45 kg N ha^{-1} surface broadcast at planting and the remaining N applied at the V9 corn developmental stage (Kitchen et al. 2017). Each plot measured 3 meters in width and 15 meters in length and followed a standardized protocol for research implementation. This protocol included site selection, weather data collection, timing and methodology for soil and plant sample collection, N application timing, N source, and N rates. More detailed procedures are outlined in Kitchen et al. (2017).

Remote sensing data collection from Proximal canopy sensor

The RapidSCAN (Holland Scientific Inc., Lincoln, Nebraska, USA) is a proximal active canopy sensor equipped with near-infrared (NIR, 780 nm), red edge (RE, 730 nm), and red light (R, 670 nm) bands. It incorporates a data recorder, visual operation interface, GPS, optical sensor, and battery. In this study, the RapidSCAN sensor was positioned approximately 0.6 meters above the corn canopy, parallel to the ground. Only the rows used for yield measurements (2-3 rows per plot, depending on the layout) were individually sensed, with their readings averaged to obtain plot-level data. The sensor's two default vegetation indices, normalized difference vegetation index (NDVI, (NIR-R)/(NIR+R)) and normalized difference red edge (NDRE, (NIR-RE)/(NIR+RE)), were selected for analysis.

Site-specific maximum return to nitrogen

Return to N (RTN) represented the net profit per hectare from applying N at a specific rate, based on data from N calibration plots or trials. The RTN calculation involves determining the yield increase due to N application (subtracting the yield without N), multiplying this by the corn price, and then subtracting the cost of N (the application rate multiplied by the N price). The cost of N fertilizer was \$0.88 kgN^{-1}, and the price of corn was \$0.158 kg $grain^{-1}$ (equivalent to \$0.40 lbs N^{-1} and \$4.00 bu^{-1}) following the protocol from Kitchen et al. (2017). In this study, we calculated the RTN for each treatment in the N calibration plots or trials. The N treatment rate that achieves the maximum RTN is known as the site-specific MRTN (MRTN).

Due to the variability in the corn-to-N price ratio, soil fertility, and weather conditions, the vegetation index (VI) corresponding to the MRTN often does not align with the highest VI observed in the calibration strips (plots). To address this, our study calculated the percentage of maximum vegetation indices at the MRTN rate for each calibration strip across various sites, states, previous crops, and the overall dataset. By averaging these percentages within each state for the same previous crop, we aim to identify site-specific MRTN threshold range for the Calibration Strip-based strategy. Additionally, the mean values and confidence intervals of MRTN from various states in the USA account for different crop rotations. These serve as the theoretical optimal N rates and ranges for each region.

A new Remote Sensing and Calibration Strip (RSCS)-based strategy

This strategy was based on calibration plots for each replicate block, which includes all N treatments ranging from 0 to 315 kg ha^{-1}, where N was considered the sole influencing factor within the block.

First, we determined the range of MRTN by plotting the vegetation index (NDVI, NDRE) response to N and identifying the maximum value of the vegetation index and its corresponding N rate. Based on the average percentage of maximum vegetation indices at the MRTN in each state for the same previous crop, the N rates could be identified that fall within the range from the maximum vegetation index to the average percentage of maximum vegetation indices on the vegetation index response to N curve. This was defined as the range of MRTN.

Secondly, to prevent excessive or insufficient in-season N application, the selected MRTN was limited to the range of regional MRTN (defined as the confidence intervals of MRTN from various states).

The strategy follows these key rules:

(1) If the range of MRTN falls within the regional MRTN range, the lowest N rate in the range of MRTN is used as the estimated MRTN.

(2) If the range of MRTN exceeds the regional MRTN range, the average value of the regional MRTN is used as the estimated MRTN.

(3) If the entire range of MRTN is either above or below the regional MRTN range, the maximum or minimum value of the regional MRTN range is used as the estimated MRTN.

(4) If there is partial overlap between the range of MRTN and the regional MRTN range, the critical point within the range of MRTN that falls within the regional MRTN range is used as the MRTN estimate.

Statistical analysis

Two different evaluations were used to implement the new strategy in predicting MRTN. The comparison was made between the preplant N application and split N treatments using the developed remote sensing and calibration strip-based strategy. To assess how well the in-season predicted MRTN matched the yield-based MRTN, a simple linear regression model was used. If the relationship was positive and significant ($P \leqslant 0.05$), the tool was considered successful in predicting MRTN. In order to determine how well the in-season predicted MRTN matched the yield-based MRTN, the mean bias error (MBE) and root mean squared error (RMSE) were evaluated based on the difference between the strategy's N recommendation and the yield-based MRTN. Another method of assessment involved examining the percentage of sites where the recommendation was close to the MRTN (Ransom et al. 2020). Recommendations within ± 45 kg N ha^{-1} of MRTN were considered 'Good,' while those within ± 90 kg N ha^{-1} of MRTN were categorized as 'Medium,' and those greater than ± 90 kg N ha^{-1} from MRTN were considered 'Poor'. A good strategy performance would be indicated by an average difference between the N recommendation and the MRTN close to zero (accurate), a low RMSE (precise), and a high percentage of 'Good' sites in total.

Results and discussion

Variability in state-specific MRTN across the US Midwest Corn Belt

The site-specific MRTN rates varied significantly across different states and previous crops (Table 1). The highest mean site-specific MRTN was observed in Missouri following soybean, while the lowest was in North Dakota following soybean and sunflower. The coefficient of variation (CV) and confidence intervals highlighted the variability within each state and crop combination. High CV values, 82% and 77% in North Dakota following soybean and sunflower, and 74% in Wisconsin following soybean, indicated a wide range of site-specific MRTN rates across sites and years.

Across all states and previous crops, the overall mean site-specific MRTN was 168 kg N ha^{-1}, with a maximum of 315 kg N ha^{-1} and a minimum of 0 kg N ha^{-1}. The overall CV was 34%, and the 99% confidence interval for the dataset ranged between 172 and 201 kg N ha^{-1}. This indicated a moderate level of variability in MRTN rates, influenced by regional factors such as soil properties, climate conditions, and previous crop history.

These findings indicated the large potential for site-specific N management strategies to optimize N use efficiency and maximize economic returns.

Table 1 Statistical results of variation in maximum return to N (MRTN) in each state, previous crop or across all dataset.

		n	MRTN (kg N ha^{-1})				
			Mean	Max	Min	CV%	CI 99%
IA	soybean	24	182	270	90	35	150–216
IL	soybean	24	219	315	90	32	184–253
IN	soybean	24	182	270	90	27	158–206

MN	soybean	23	198	270	90	26	170–223
MO	soybean	28	241	315	135	22	215–267
ND	corn	16	183	315	45	39	138–228
ND	soybean	4	45	90	0	82	11–79
ND	sunflower	4	56	90	0	77	11–90
NE	corn	4	146	270	45	68	56–248
NE	soybean	20	200	315	45	40	153–243
WI	soybean	24	131	315	0	74	84–184
Overall		195	186	315	0	34	172–201

Note: The n represents the number of repeated blocks; The CV is the abbreviation for Coefficient of Variation (%); The CI 99% stands for a 99% confidence interval.

RCS-based in-season prediction of MRTN

The relationship between the predicted site-specific MRTN using NDVI and NDRE and observed site-specific MRTN rates using corn yield across all states and previous crops is shown in Fig. 1. RSCS-based PNM using NDVI and NDRE could estimate site-specific MRTN rates quite well, with R^2 values ranging from 0.44 to 0.48. The NDRE-based strategy performed slightly better (R^2=0.48) than the NDVI-based strategy (R^2=0.44). The data points in the NDRE plot were more tightly clustered within the green shaded region of 45 kg N ha^{-1}, indicating a slightly better fit. than NDVI.

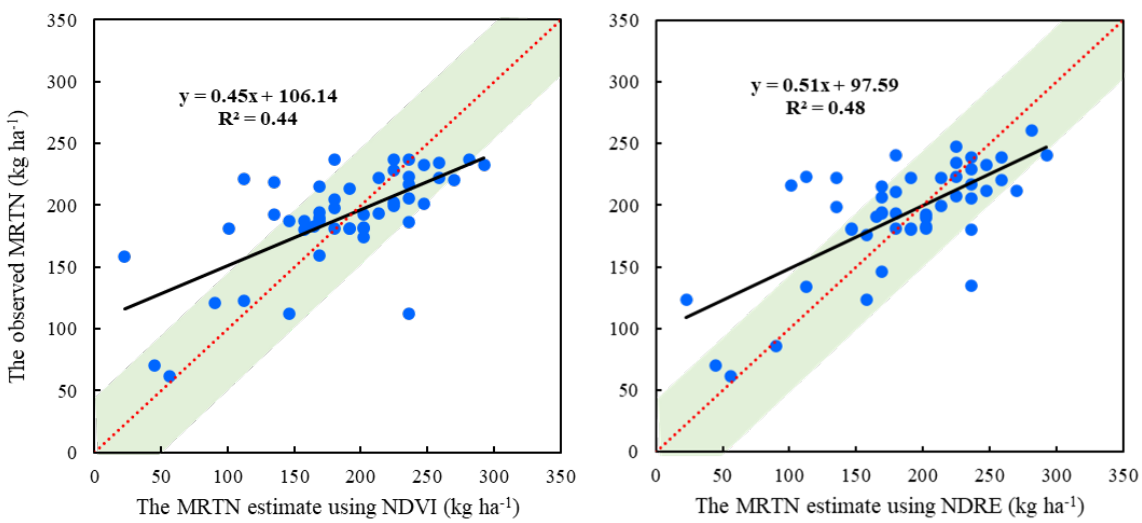

Fig 2. Validation results for the MRTN estimate using NDVI and NDRE across all N rates, varieties, stages, and years.

(The green shaded region indicated the 'good' predicted performance within ±45 kg N ha^{-1} of MRTN)

The RSCS-PNM strategy VS Farm N practice

The RCS-based precision N management strategies using NDVI and NDRE performed similarly, but both outperformed the farmer N practice (FNP) in terms of reducing bias and improving accuracy in MRTN estimation (Table 2). Compared to the FNP, which tended to overestimate MRTN, NDVI and NDRE-based RSCS-PNM strategies showed both overestimation and underestimation of N needs in the all-preplant application and split application, respectively. Moreover, both RSCS-based PNM strategies demonstrated lower RMSE values (43–50 kg N ha^{-1}) compared to FNP (62–66 kg N ha^{-1}) across different N application methods. The percentage of 'Good' sites (65–78% within ±45 kg N ha^{-1}) was significantly higher for the RSCS-based PNM strategies than for FNP (55–67%) in both preplant and split applications. Overall, the RSCS-based PNM strategies can provid more accurate and precise site-specific MRTN estimates compared to the traditional farmer N practice.

Table 2 The precision and accuracy of remote sensing and calibration strip (RSCS)-based strategy using mean bias error

(MBE), Root Mean Square Error (RMSE), and the percentage of 'Good' sites (<±45 kg N ha^{-1}) in total.

	Preplanting			Split		
	MBE Kg N ha^{-1}	RMSE	Good %	MSE Kg N ha^{-1}	RMSE	Good %
FNP	9	66	67	8	62	55
RCS based PNM						
Using NDVI	4	45	76	-15	50	65
Using NDRE	7	43	78	-13	49	67

Note: FNP: Farmer nitrogen practice; RCS based PNM: Remote Sensing and Calibration Strip (RCS)-based precision nitrogen management strategy.

Conclusion

This study revealed significant variability in site-specific MRTN rates across the US Midwest Corn Belt, influenced by previous crops and regional factors. Missouri had the highest averaged site-specific MRTN following soybean, while North Dakota had the lowest average site-specific MRTN following soybean and sunflower. High CV values indicated substantial site-specific MRTN variability within states. The overall mean MRTN was 168 kg N ha^{-1}, with an overall CV of 34%. RSCS-based PNM using NDVI and NDRE estimated site-specific MRTN rates with moderate accuracy (R^2 = 0.44 to 0.48). NDRE performed slightly better than NDVI, explaining more variability in measured MRTN. Both RSCS-based strategies using NDVI and NDRE outperformed the farmer nitrogen practice in reducing bias and improving accuracy, with lower RMSE values (43–50 kg N ha^{-1}) compared to farmer N practice (62–66 kg N ha^{-1}). The percentage of 'Good' sites was higher for RSCS-based strategies (65–78%) than FNP (55–67%). More studies are needed to further evaluate and improve this new strategy under diverse on-farm conditions.

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