Final Report for AFREC & Minnesota Department of Agriculture Pesticide

& Fertilizer Management Division

Developing Distinct Levels of Precision Nitrogen Management Strategies & Technologies for Corn in Minnesota

AFREC R2019-20

PRINCIPLE INVESTIGATOR/PROJECT MANAGER: **Yuxin Miao**

VENDOR/CONTRACTOR/ORGANIZATION: **University of Minnesota**

Project objectives:

1) Develop calibration strip-based PNM strategies for corn;
2) Develop crop growth model-based PNM strategies for corn;
3) Evaluate new proximal and UAV remote sensing systems for early and better diagnosis of corn nitrogen (N) status and develop crop sensing-based PNM algorithms and strategies;
4) Develop integrated PNM strategies for corn by combining crop modeling and remote sensing technologies;
5) Conduct on-farm experiments to evaluate distinct PNM strategies for the potential benefits in terms of corn yield, NUE, profitability and N losses.

Field and experiment design of 2019

Three experiment sites were chosen in the corn growing season of 2019, including one research station of University of Minnesota, Wells Agriculture Experiment Station, and two private farms (Fig. 1). Randomized complete block design is adopted to study temporal spectral feature response to N of corn with three treatments (tillage, drainage, and N) at the Wells Agriculture Experiment Station. We conducted randomized strip block design for calibration strip-based PNM strategies at the two farms and testing other PNM strategies (Fig. 2). Because of no urea available for preplant N application, the preplant N application were postponed about two weeks after planting in Farm B. During N side-dress, variable rates of N in sub-strips assist in validating strip-based PNM methods and exploring the gap of optimal N rates across PNM strategies at the scale of landscape levels. Totally, 24 sampling points in four transects at Farm A, 30 sampling points in five transects at Farm B are assigned to monitor corn growth stages, biomass, tissue N, height, and nitrate level in soil.

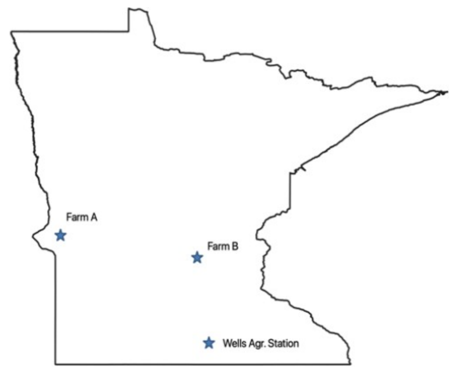
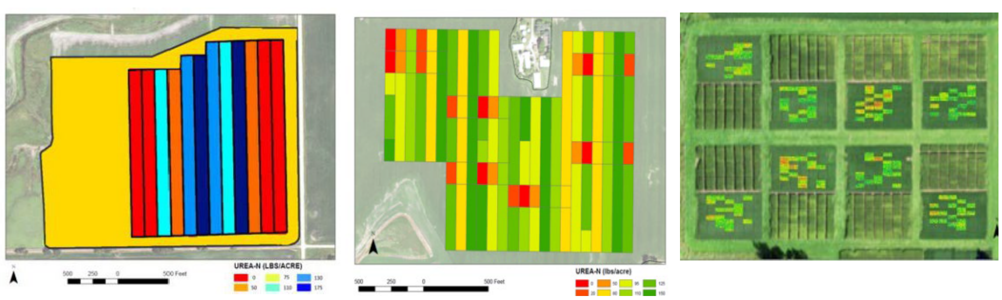


Fig. 1. Location of the three experiment sites in the growing season of 2019.



(a) (b) (c)

Fig. 2. Randomized strip block design for N treatments, Farm A (a), Farm B (b), and randomized complete block design of three treatments (drainage, tillage and N rates) at Wells Experiment Station (c). Six N rates for preplant are in Farm A, and eight N rate after planting for Farm B.

Methods & analysis:

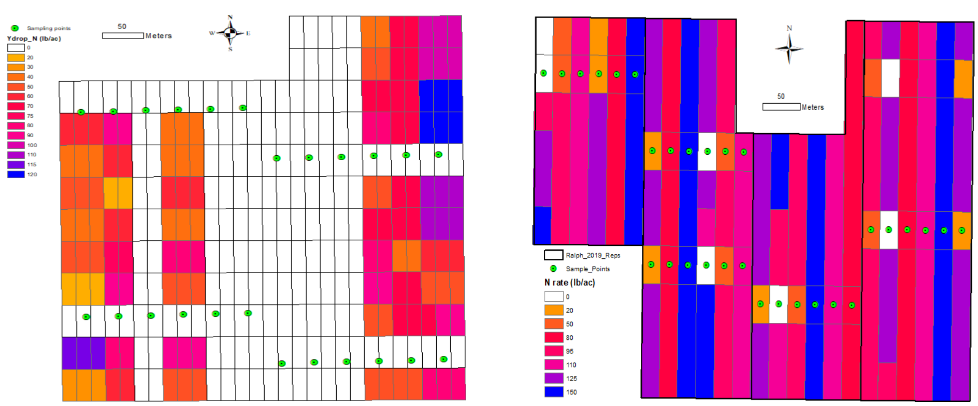
Temporal spectral features across four sensing platforms during different growth stages are monitored at the scales of leaf, canopy and field levels in the three experiment sites. The four platforms are shown in Fig. 3. They are equipped with different sensors to measure various spectral variables that potentially correlate corn N status at leaf and canopy levels (Table 1). Multiple measurements associated with corn growth stages (V5-V6, V8-V10, V12, VT/R1, R3, R6) for spectral features at the three locations have been or will be conducted (Table 2).

(a) (b) (c) (d)

Fig. 3. Four proximal/remote sensing platforms for corn spectral monitoring of N status: the force-A Dualex at a level of corn leaf (a), the Cropcircle Phenom at a level of corn canopy (b), the Tetracam camera at levels of canopy and field (c), and the Quantix at levels of canopy and field (d).

Soil samples at two depths (0-15 cm or 0-6", and 15-30cm or 6-12'') for all the monitoring sites of the transects at the two farms and all treatment plots at the Wells Experiment Station have been collected for soil nitrate concentration analysis during preplant and before side-dress. We measured the soil moisture, soil temperature, and salinity for a depth of 0-20 cm or 0-8''. Plant samples before side-dress are also collected for biomass and tissue N analysis.

Side-dress N applications were conducted with UAN on 7/22/2019 at Farm A and with urea on 7/8/219 at Farm B. Amount of side-dress N was determined by nitrogen sufficient index generated from strip zones and balanced with MRTN of Minnesota (Fig. 4). Remote sensing data with UAV-Quantix were collected during V12, VT and R3.



(a) (b)

Fig. 4. Side-dress N application for Farm A (a) and Farm B (b) in 2019.

With the experiment design, final plant and soil samples were collected on 10/31/2019 at Farm A and 10/29/2019 at Farm B. The harvest dates are 11/10/2019 in Farm A, and 11/5/2019 in Farm B. Corn plants of the two farms were killed before maturity due to frost and snow during the early of October. The examination of ears and kernels indicated that kernel moisture was high, and many kernels did not reach R6. Yield maps based on management grids are shown in Fig. 5.

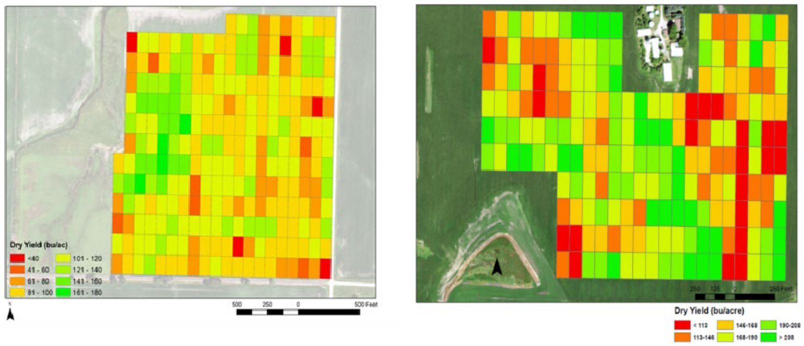


Fig. 5. Corn yield variability of Farm A (left) and Farm B (right) in 2019.

Agronomic optimal nitrogen rates (AONR) were calculated for total 57 N-rate ramps on the Farm A (Fig. 6 left) and Farm B (Fig. 6 right). The farms showed very different on ramp yield responses to N rates. Yield responses to N rates were only found in the 12 of total 24 ramps in Farm A, but 31 of total 33 ramps in Farm B. Two examples from the two farms are shown in Fig. 7. The overall low yield response to N rate in Farm A is mainly due to the abnormal wet year and no drainage system. Direct field observations from Farm A indicated that over 10 sites with water ponding existed across nearly whole growing season. The long-term saturated soils under water ponding in Farm A caused severe damages on root growth and development as well as nutrient update, and significantly exacerbated N loss through denitrification and leaching.

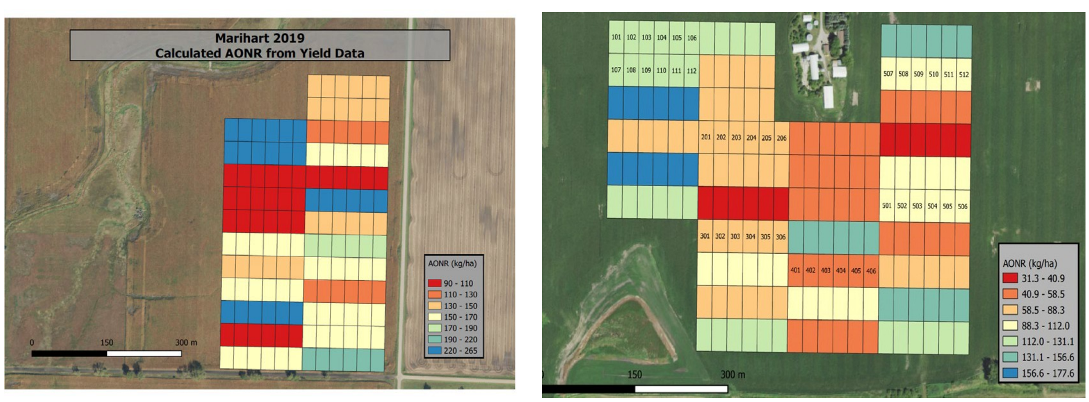


Fig. 6. Agronomic optimal N rates (AONR) in 24 N ramps of Farm A (left) and 33 ramps in Farm B (right).

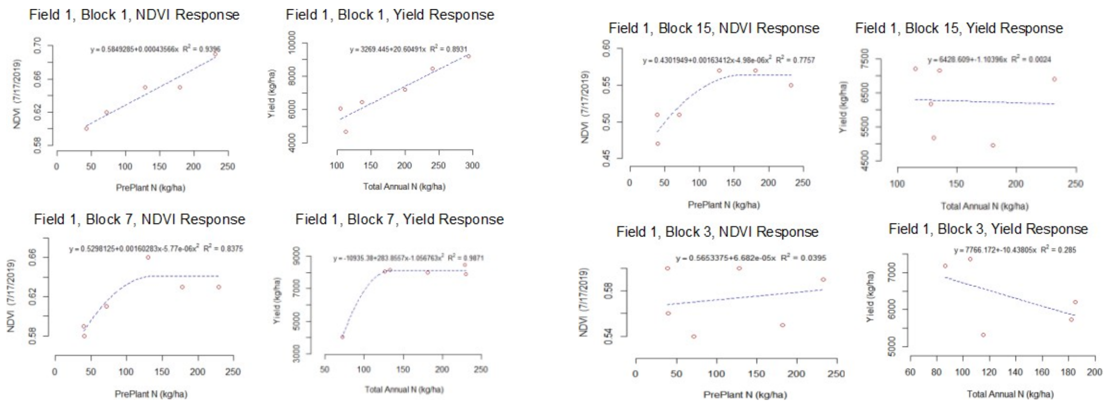


Fig. 7. Examples of agronomic optimal nitrogen rates (AONR) calculations in the two experiment farms.

Project progress:

- *<u>Objective 1</u> – Develop calibration strip-based PNM strategies for corn*

Based on this year's preliminary results, we proposed the In-season Site-specific Calibration Strip (ISCS)-based PNM strategy as illustrated in Fig. 8. This strategy is a very promising and practical PNM strategy that can be easily implemented by farmers. It will be further evaluated in 2020.

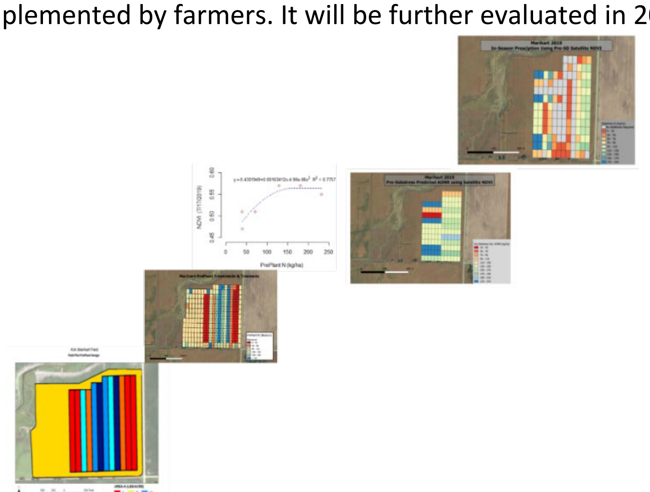


Fig. 8. The concept of In-season Site-specific Calibration Strip (ISCS)-based precision N management strategy.

The comparison of economic return between ISCS-based precision N management rates and famer's N rate indicated that our management rates were able to help farmers to improve economic return. In Farm B, only 23 of 144 grids showed equal or lower return than farmer's rates (Fig. 9left). The low return blocks usually occurred with water ponded areas or replant areas, particularly for Farm B.

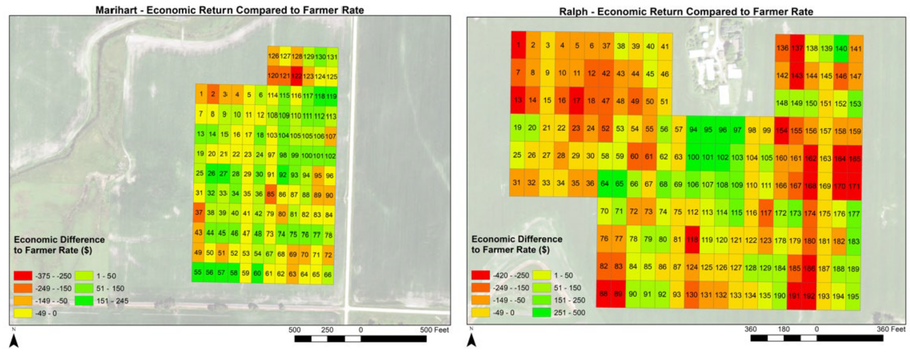


Fig. 9. Economic return comparison between experiment rates and farmer's rate in Farm A (left) and Farm B (right).

- *Objective 2 - Develop crop growth model-based PNM strategies for corn*

Four crop models including Adapt-N, APSIM, DSSAT, and Maize-N would be evaluated for their capability of corn precision nitrogen management. The model, Adapt-N, is a commercialized one, and Yara is unwilling to join the research so that the model is removed in this study. The Maize-N model generates only optimal nitrogen recommendation rates for a specific year and site without detailed outputs of nitrogen dynamics. Irrigation management isn't included in Maize-N. These three models were evaluated in this study using four nitrogen rate experiments conducted in MN (Fig. 10).

Genetic parameters of corn hybrids were provided by Pioneer for model calibration in APSIM and DSSAT. Simulation results on nitrogen dynamics and usage from the models of APSIM and DSSAT were compared with the measured results. We evaluated maximum return to nitrogen (MRTN) of three models and experiments. The values of $4.0/bu corn and $0.4/lb N are applied as baseline for MRTN analysis in this study.

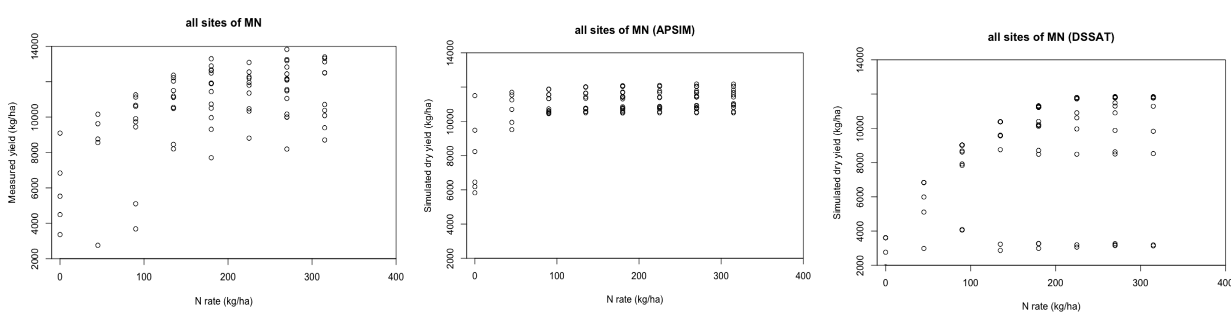


Fig. 10. Observed and simulated corn yield responses to fertilizer N input at the four sites of Minnesota, observed yield (left), simulated yield by APSIM (middle), and simulated yield by DSSAT (right). There were no measured yield data available at Richland during 2014.

Observed yield responses to nitrogen fertilizer rates indicated high variability at different sites and years (Fig. 10). The APSIM model did not show sensitive yield response to nitrogen inputs. After over 100 kg/ha N, yield reached plateau, and the variability due to site and year was less than the observed and the simulated variability by DSSAT. Although the simulated pattern from DSSAT was less variable, it demonstrated more similarity to the observed pattern. Surprisingly, the DSSAT model successfully simulated the failure year of 2014 at New Richland (Fig. 10right), but not by the APSIM.

The observed and simulated MRTN values were compared under preplant N only and split-N applications (preplant plus sidedress) at different sites and years. Under preplant N application only, the MRTNs simulated by the CERES-Maize model in DSSAT were more similar to the measured MRTN than the APSIM model (Fig. 11). MRTN was significantly over-estimated by APSIM at Waseca during 2016. Both models clearly under-estimated MRTN by about 70 kg/ha at Becker under irrigation at Becker. Under split-N treatment, the Maize-N model predicted lower MRTN compared with the observed or the simulated MRTNs by APSIM and DSSAT models (Fib. 12). The patterns of MTRN simulated by APSIM and DSSAT were similar to those of preplant N treatment.

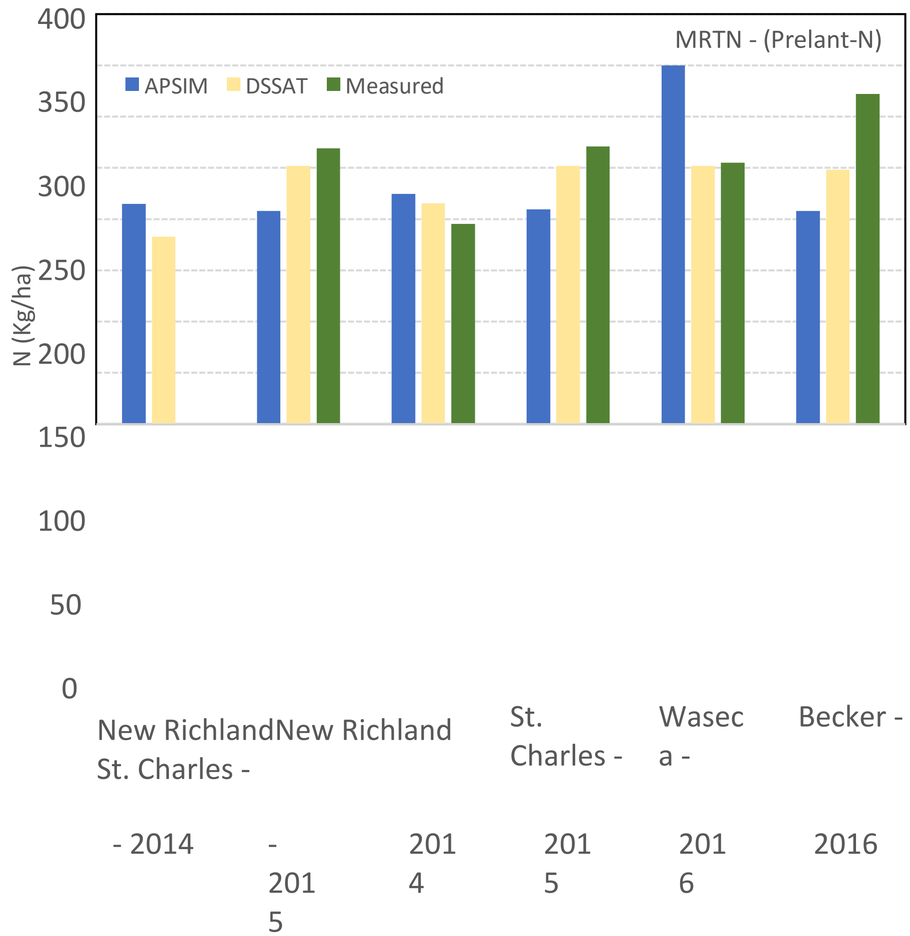


Fig. 11. Comparison of observed and simulated MRTN under the treatments of preplant N fertilizer only at the four sites during three different years (2014, 2015 and 2016). Maize-N is not included because of split-N fertilization only.

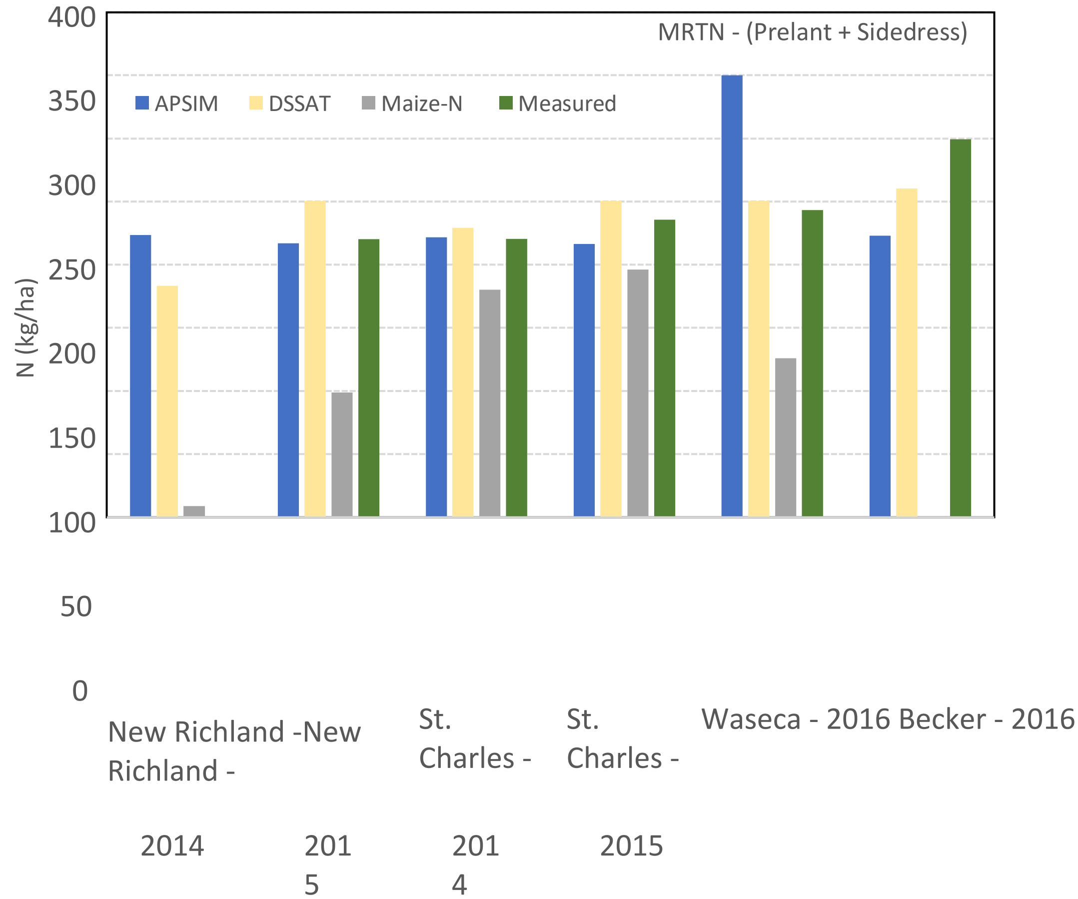


Fig. 12. Comparison of observed and simulated MRTN under the N treatments of both preplant and side-dress at the four sites during three different years (2014, 2015 and 2016).

Further comparison of MRTN between the observed and simulated by three models was conducted. The APSIM model had greater absolute MRTN differences under preplant N treatment only for all sites and years compared with DSSAT, about 45.5 kg/ha (Table 1). Under the preplant plus side-dress N treatments, DSSAT showed a better performance of MRTN simulation than APSIM and Maize-N models, only with a difference of 19.9 kg/ha.

We also compared the absolute difference between preplant N and split-N (preplant+sidedress) treatments among the three models (Table 2). The measured difference was about 28.6 kg/ha, but the simulated difference by APSIM and DSSAT was less than 6.8 kg/ha. This suggests that the APSIM and DSSAT model are not very sensitive to N application methods such as preplant only or split-N application.

Overall, DSSAT had a better performance of N dynamics and responses than the other two models, and it has the potential for in-season MRTN estimation. Further evaluation of the variability simulation under different N treatments is needed to better understand the mechanism behind and model improvement.

Table 1. Absolute difference of MRTN between the simulated and measured under preplant and side-dress N treatment.

	Preplant-N only		Preplant-N + Side-dress-N		
	APSIM	DSSAT	APSIM	DSSAT	Maize-N
	..........- *kg ha^{-1}* ------------				
New Richland - 2015	61.2	17.2	3.1	30.2	121.3
St. Charles - 2014	29.0	20.0	1.2	8.5	40.5
St. Charles - 2015	61.6	19.2	19.3	14.5	39.7
Waseca - 2016	95.0	3.1	106.7	7.1	117.2
Becker - 2016	114.4	74.0	76.4	39.2	
Mean	72.2	26.7	41.3	19.9	79.7

Table 2. Absolute MRTN difference between preplant-N only and prelant+sidedress N treatments

	Measured	APSIM	DSSAT
	..........-*kg ha^{-1}*------------		
New Richland - 2015	48.5	9.2	1.5
St. Charles - 2014	25.8	2.5	13.8
St. Charles - 2015	34.4	7.1	1.5
Waseca - 2016	11.3	0.0	1.5
Becker - 2016	22.8	15.2	12.0
Mean	28.6	6.8	6.1

- *Objective 3 - Evaluate new proximal and UAV remote sensing systems for early and better diagnosis of corn N status and develop crop sensing-based PNM algorithms and strategies:*

  The Quantix hybrid UAV remote sensing system was found to be very flexible and practical for monitoring corn growth and N status at a spatial resolution less than 10cm. The PlanetScope satellite remote sensing at 3 m spatial resolution and daily revisit time also provides a practical tool for guiding in-season N management of corn at farm level.

With the randomized complete block design at Wells, three factors (N, drainage and tillage) were included to examine N use efficiency and interactions with drainage and tillage. Preliminary analysis with drainage and conventional tillage (Fig. 13), and no-drainage and no-till (Fig. 14) indicated that the Dualex sensor was able to clearly detect N stress with the four measured variables, chlorophyll, flavonoid, anthocyanins, and nitrogen balanced index (NBI) at the low N rates from 0 to 80 lb/ac during V7. The quadratic or quadratic plateau model could be used to describe the quantification relationship between N rates and different variables from Dualex sensor.

The preliminary statistical analysis indicates that N rates significantly affect all measured variables, contents of chlorophyll, flavonoid and anthocyanins from Dualex (Table 3). Drainage has significant effects on chlorophyll, anthocyanins and NBI, but not on flavonoids. Only the content of anthocyanins is affected by tillage. The detailed analysis under different N rates and drainage/tillage is ongoing.

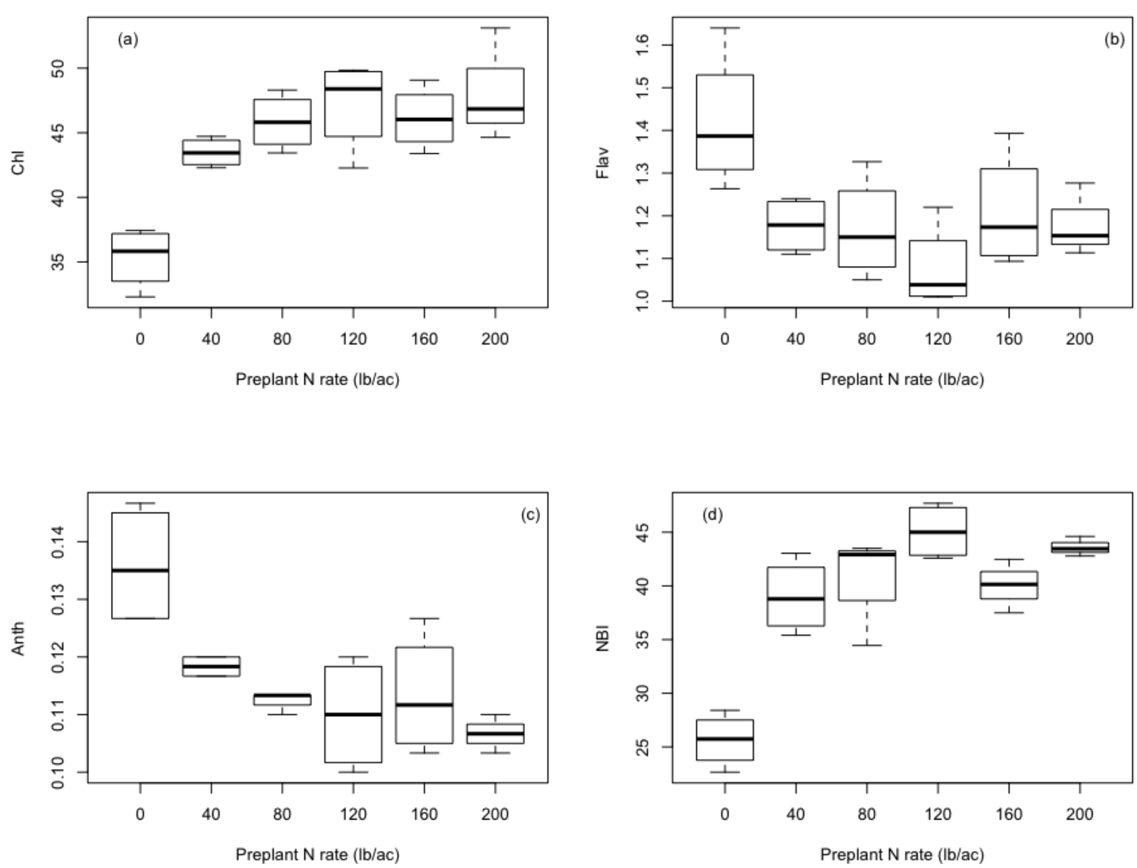


Fig. 13. The corn leaf chlorophyll, flavonoid and anthocyanins concentrations and nitrogen balance index (NBI) at different N rates under drained conventional till conditions at V7 stage in the Wells Experiment.

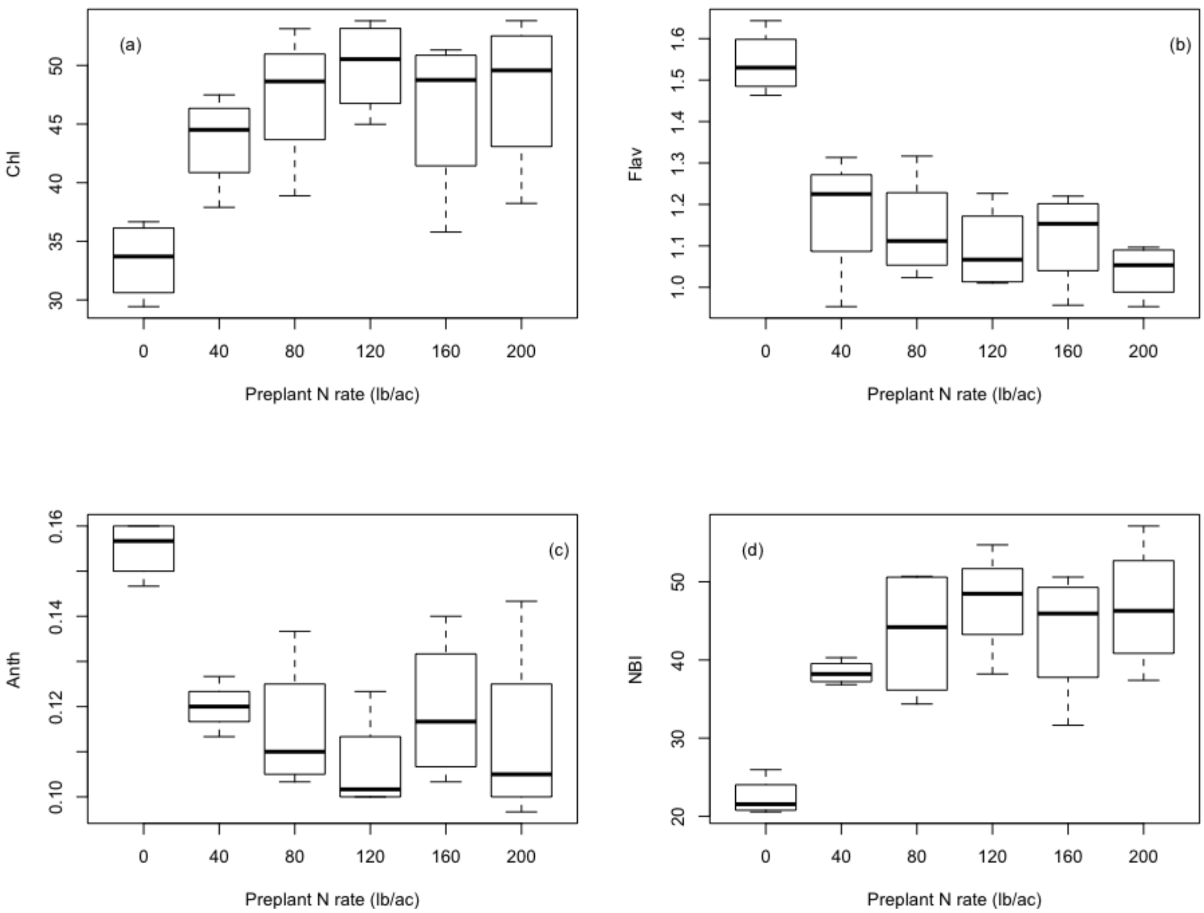


Fig. 14. The corn leaf chlorophyll, flavonoid and anthocyanin concentrations and nitrogen balance index (NBI) at different N rates under undrained no-till conditions at the V7 stage in the Wells Experiment.

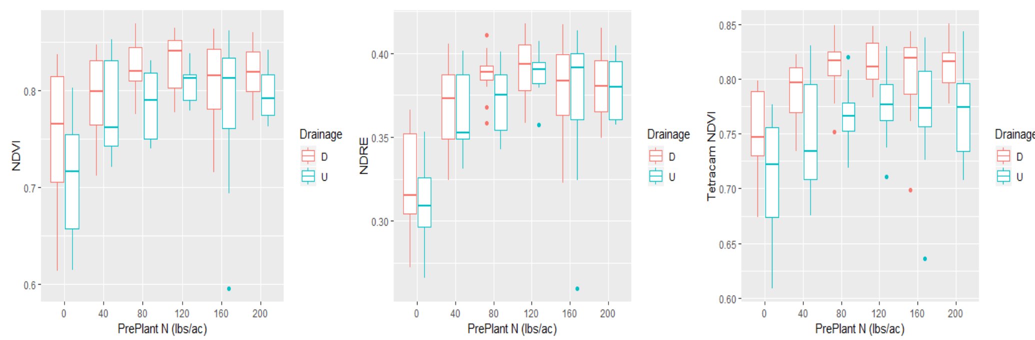
Table 3. Summary of split-split plot ANOVA results (F-values) for the Dualex measured variables at Wells, MN during V7 in 2019.

Factor	Block (B)	Drainage (D)	Tillage (T)	N rates (N)	D×T	T×N	D×N	D×T×N
DF	3	1	2	5	2	10	5	10
Chl	1.38^{ns}	13.17^{**}	2.94^{ns}	16.90^{**}	4.58^{*}	2.11^{*}	1.79^{ns}	0.54^{ns}
Flav	0.44^{ns}	2.44^{ns}	2.75^{ns}	8.89^{**}	1.91^{ns}	0.35^{ns}	0.71^{ns}	1.32^{ns}
NBI	0.80^{ns}	5.79^{*}	1.62^{ns}	7.41^{**}	1.45^{ns}	1.49^{ns}	1.02^{ns}	1.37^{ns}
Anth	2.43^{ns}	0.29^{ns}	4.76^{*}	14.59^{**}	3.39^{*}	0.76^{ns}	1.26^{ns}	1.08^{ns}

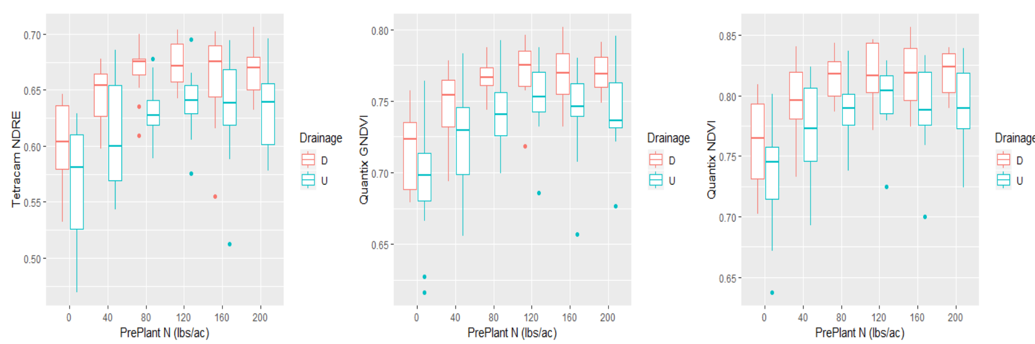
Block, Drainage, Tillage and N rates are abbreviated B, D, T and N, respectively, in the interaction terms. ns: not significant (P>0.05); *, **: significant at P < 0.05 and P < 0.01, respectively.

Spectral features (NDVI, GNDVI and NDRE) of three remote sensing platforms (Crop Circle Phenom, UAV with Tetracam camera, and Quantix UAV system) were analyzed for six N rates (0, 40, 80, 120, 160, 200 lb/ac) under the treatments of Drainage (Fig. 15) and Tillage (Fig. 16) at V7 stage. The values of all three spectral values with drainage were consistently greater than those without drainage under the same N rate management. This indicated that the growth status with drainage was improved compared with no drained plots, although high variability was observed.

We find that the values of all three spectral indices reach plateau after the N rate of 80 lb/ac for the drained plots, but after 120 lb/ac for undrained plots. Less N loss and improved N use efficiency under drained soil would lead to less N stress and improve growth status during V7. Statistical analysis is needed to further confirm this result.



(a) (b) (c)



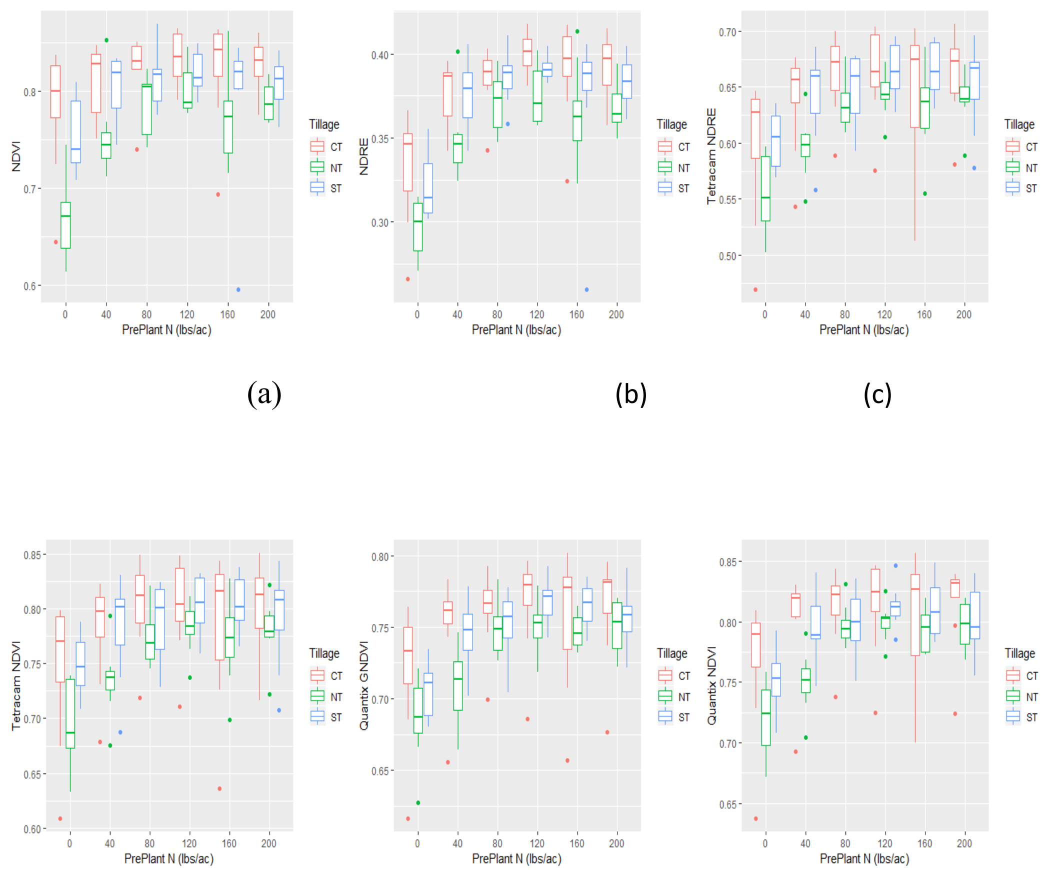
(d) (e) (f)

Fig. 15. Variability of spectral features (NDVI, GNDVI and NDRE) of three remote sensing platform, Crop Circle Phenom (a and b), UAV with Tretracam camera (c and d) and Quantix UAV system (e and f) with and without drainage management at Wells, MN at the V7 stage (7/8/2019).

Under three tillage treatments (conventional-till, no-till, and strip-till), the spectral index values showed the same trend at a certain N rate (Fig. 16). The plots under conventional tillage had the greatest values of NDVI, NDRE and GNDVI among all three tillage treatments, while the no-till system had the least vegetation index values. This suggested that tillage management had direct impacts on soil N immobilization-mineralization and plant available N, as has been widely recognized. Similarly, the vegetation index values generally reached plateau at the N rate of 40-

80 lb/ac. We did not observe significant difference of NDVI, NDRE and GNDVI after the N rate of 120 lb/ac.

The preliminary results show that the platform of Tetracam seems to have better capability of differentiating managements than that of Quantix (Fig. 17). The difference or sensitivity of spectral features between indices and platforms are under further investigation. Interestingly, the spectral analysis in the study directly catch the effects of N rates, treatments of drainage and tillage, and this will help to better quantify spatial and temporal variability/patterns and predict future N patterns. Moreover, we are able to detect and diagnose N status and growth status through the spatiotemporal analysis based on cross-platform remote sensing.



(a) (b) (c)

(d) (e) (f)

Fig. 16. Variability of spectral features (NDVI, GNDVI and NDRE) of three remote sensing platform Crop Circle Phenom (a and b), UAV with Tetracam camera (c and d) and Quantix UAV system (e and f) under conventional tillage (CT), strip-till (ST) and no-till (NT) management at Wells, MN at the V7 stage (7/8/2019).

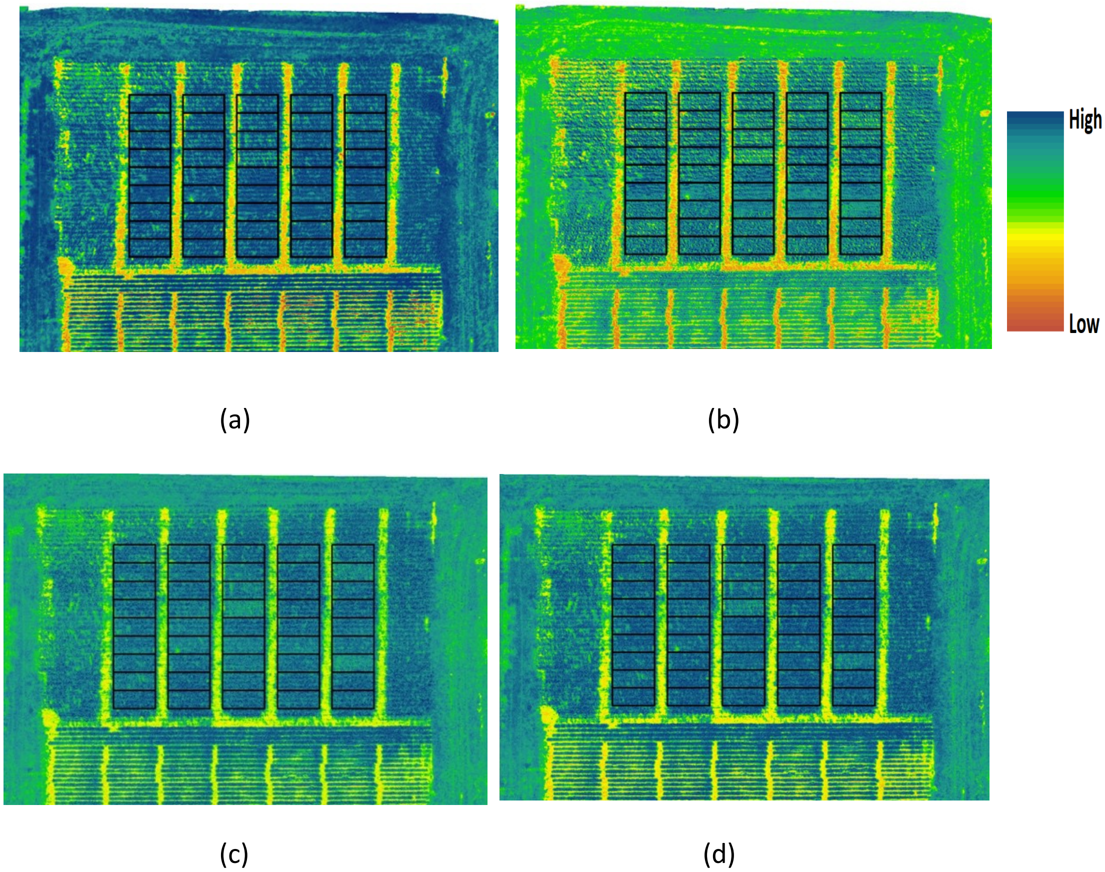


Fig. 17. Variability of spectral features from UAV with Tetracam camera, NDVI (a) and NDRE (b), and Quantix UAV system, GNDVI (c) and NDVI (d) for Block 1 (Drained) at Wells, MN at the VT stage (7/23/2019).

We explored machine learning modeling to understand the relationship between soil and landscape features, remote sensing, and yield variability (Fig. 18). Totally, 15 variables were included for the analysis. The random forest (RF) algorithm was applied in this study. The preliminary study showed that RF (Fig. 18) could catch the yield variability affected by soil, landscape and remotes sensing variables. Variable importance analysis indicated that remote sensing data (NDVI) was a dominant variable of yield variability (Table 4), and then slope and elevation. Soil variables usually contributed to yield variability less than 8%. A machine learning-based precision N management strategy is being developed.

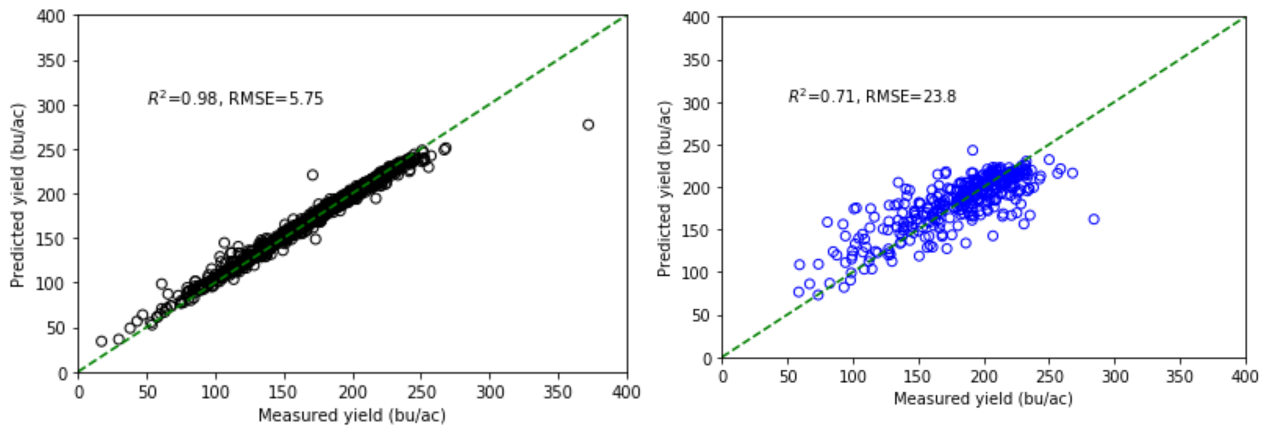


Fig. 18. Using the random forest algorithm to explore yield variability as affected by soil, landscape, and remote sensing, the random forest algorithm for Farm.

Table 4. Relative importance of key factors influencing corn yield variability based on random forest model for Field B in 2019.

Variable	Weight
NDVI	**0.30**
Elevation	**0.08**
pH	**0.07**
Slope	**0.06**
OM	**0.06**
K	**0.06**
CEC	**0.05**
TWI	**0.05**
P	**0.04**
Sidedress N_Rate	**0.04**
Aspect	**0.04**
Contribution.area	**0.04**
Ksat	**0.04**
curvature	**0.03**

- *Objective 4. Develop integrated PNM strategies for corn by combining crop modeling and remote sensing technologies;*

  Research for this objective will be conducted in 2020.

- *Objective 5. Conduct on-farm experiments to evaluate distinct PNM strategies for the potential benefits in terms of corn yield, NUE, profitability and N losses.*

  Field experiments will be conducted for this objective in 2011.

Outreach

Our graduate student working on this project, Cadan Cummings, gave a presentation at the ASA-CSSA-SSSA Annual Meeting in San Antonio, TX. The presentation information is listed below:

Cummings, C.*, Miao, Y., Fernández, F. G., & Paiao, G. D.* Evaluating Crop Circle Phenom Active Canopy Sensor for Corn Nitrogen Status Diagnosis in Minnesota. Madison, WI: ASA- CSSA-SSSA. [Non-Refereed] Annual ASA-CSSA-SSSA Meeting, Nov. 10-13, 2019, San Antonio, TX.

We organized a Project Meeting inviting the cooperative farmers and crop consultant to have a project meeting to share what we have done, what we learned and how we can help the farmers to improve their management on Jan. 7, 2020 (Fig. 19). The farmers really enjoyed this meeting and would love to continue to work with us in 2020.

Fig. 19. Project meeting involving cooperative farmers, crop consultant, researchers and graduate students on Jan. 7, 2020.