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

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## BACKGROUND

Precision nitrogen (N) management (PNM) aims to match N fertilizer supply with crop N demand in both space and time, and thus has great potential to improve N use efficiency (NUE), increase farmer profitability, and reduce N losses and negative environmental impacts. However, current adoption rate of PNM is still low in Minnesota corn production, and most farmers apply all N fertilizer before planting. This may be due to the knowledge background of the growers, high cost and complexity of current PNM technologies, lack of technology support, and the weaknesses and limitations of some of the available PNM technologies, etc. To overcome some of these barriers, this project aims to develop distinct levels of PNM strategies and technologies to facilitate the adoption of PNM by Minnesota corn producers.

For producers who are more risk-averse, calibration strip-based PNM strategies can be used to guide field-specific uniform or site-specific variable rate N applications without previous database establishment. Crop growth models can be calibrated, validated and used to determine optimum N rates of corn for different soil types and regions of Minnesota based on long-term simulations using historical data. It can also be used to guide in-season N management decisions based on current season and historical weather data. For more risk-tolerant producers, innovative new sensing technologies including leaf chlorophyll fluorescence sensor - Dualex Scientific+, light handheld multispectral canopy sensor – RapidSCAN CS-45, the integrated multi-parameter canopy sensor - Crop Circle Phenom UAV and satellite remote sensing can be used for early and more accurate detection of corn N stress, and differentiation of N vs. other abiotic stresses like water. More advanced integrated PNM strategies will be developed based on current and new sensing technologies, crop growth modeling and their combinations.

## PROJECT OBJECTIVES

1) Develop and evaluate calibration strip-based PNM strategies for corn;
2) Develop and evaluate 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 and evaluate integrated PNM strategies for corn by combining crop modeling and remote sensing technologies;
5) Explore management zone-based (MZ) PNM technology

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

## KEY PROGRESSES

### 1. Developing a remote sensing and calibration strip-based in-season nitrogen management strategy for corn


**Abstract**

The objective of this research was to develop and evaluate a remote sensing and calibration strip-based in-season corn (*Zea Mays* L.) nitrogen (N) recommendation strategy guided by unmanned aerial vehicle (UAV), aerial or satellite remote sensing platforms. Three commercial farm fields in Minnesota, USA were selected to evaluate the proposed in-season N recommendation technique at the corn growth stage of around V8. The results indicated that 60-90% of the block-specific optimum N rates (ONRs) based on any two different platforms were within 10 kg $ha^{-1}$ of each other using the recommendation method. Overall, the calibration strip method successfully increased N use efficiency (NUE) at all three sites, while maintaining yields comparable to applying farmer N rates at two of the three site-years.


**Introduction**

In-season site-specific corn (*Zea Mays* L.) nitrogen (N) recommendations are very challenging because they are directly influenced by spatial and temporal patterns of crop N demand and soil N supply, which can significantly fluctuate within and between fields (Scharf et al., 2001; Cao et al., 2017). Successful recommendation strategies must adjust for seasonal N cycling from mineralization, previous crop fixation, and additions of inorganic N from manure or synthetic fertilizers while also considering the fluctuating crop demand of N throughout their vegetative and reproductive growth cycles (Robertson & Vitousek, 2009). Consequently, timing N availability to occur when corn N demand is highest through delaying a majority of fertilization until growth stages V8-V9 has been promoted because it provides for dynamic control of N inputs based on seasonal weather (Feinerman et al., 1990).

The ramp calibration strip (RCS) strategy was proposed to be a practical N management approach (Raun et al, 2008). With the implementation of calibration strips, seasonal and spatial N dynamics can be examined at each individual crop stage to estimate in-season optimum N rates (ONRs) within the field. RCS-based N recommendation can estimate the N needs and avoid the requirement to determine each N cycle component individually (i.e. mineralization, leaching, denitrification). However, further research questioned the reliability of this strategy using 1 or 2 sets of RCSs to guide in-season N application across a large field, due to significant within-field variability (Roberts et al., 2011). The objectives of this study were to 1.) develop a calibration strip-based precision N management strategy that can determine site-specific ONRs for corn around V8 growth stage using remote sensing; and 2.) evaluate unmanned aerial vehicle (UAV), aerial, and satellite sensing platforms for making in-season N recommendations based on calibration strips.

## Materials and Methods

### Site description

Three trials were conducted in commercial farm fields in Minnesota, USA. All fields were rain-fed and were in a corn-soybean (*Glycine max* L.) rotation. Field 1 (F1) trial was conducted during 2019 and was located in western Minnesota in a field with 0-2% slope and soil textures primarily composed of Flom-Aazdahl-Hamerly complex and Bearden silt loam. Field 2 (F2) trial was also located in western Minnesota and conducted during 2020 in a field characterized by heterogenous soil textures comprised of Croke very fine sandy loam, Doran-Mustinka silty clay loam, and Fargo silty clay loam. F2 possessed moderate topographic variation due to several drainage paths cutting through the field. Field 3 (F3) trial was conducted in eastern Minnesota during 2020 and the soil textures in the field mainly consisted of a combination of Lester loam, Angus loam, and Glencoe clay loam with 0-10% slope.

### Experimental design

Calibration strip trials with five repeating field length N rates were implemented in each field at pre-plant. Nitrogen treatments were applied based on farmer N rate (FNR) and consisted of treatments of 0%, 35%, 70%, 100%, and 130% FNR. Each field trial was fertilized using granular urea (46-0-0, N-P-K) broadcast directly before planting and incorporated to eight centimeters depth using tillage. Due to the addition of N from other fertilizers broadcast together with urea at pre-plant, such as monoammonium phosphate (11-52-0, N-P-K) and ammonium sulfate (21-0-0-24, N-P-K-S), no field trial was successfully implemented with 0 kg-N $ha^{-1}$ treatments and each was closer to 10-20 kg $ha^{-1}$ N starter fertilizer. Unlike previous calibration strip testing that used one or two strips per field, the whole field area was divided into calibration strips for this study. Field trials were closely observed at around V8 growth stage to estimate in-season site-specific ONR using remote sensing technology. To summarize fertilizer applications and flight operations, the field was divided into a virtual reference grid. The virtual grids were approximately 49 m long and 24 m or 18 m wide to match in-season N applicator width. Five adjacent grids that represented the range of pre-plant N treatments were combined to form calibration response blocks to estimate in-season site-specific ONR. To evaluate the effectiveness of RCS's and the yield potential of applying very low annual N, four calibration blocks were selected in each field as check areas that received the normal five pre-plant rates, however, would not receive in-season N. These four blocks were selected due to soil texture composition, topography, and seed germination.

### Remote sensing measurements

Three remote sensing platforms were used to monitor the field trials around V8 growth stage, including AeroVironment Quantix Mapper UAV (AeroVironment Inc. Semi Valley, CA, USA), Ceres Imaging airplane (Ceres Imaging, Oakland, CA, USA), and Planet Labs PlanetScope satellite (Planet Labs, San Francisco, CA, USA) remote sensing systems. All three systems image multispectral bands that are corrected to relative surface reflectance and subsequently used to calculate normalized difference vegetation index (NDVI). The main difference between the three platforms is spatial resolution, which ranged between 0.05 m for the Quantix Mapper up to 3 m for PlanetScope satellite imagery (Table 1). To prepare the data for comparison analysis, QGIS

(QGIS Development Team, 2020) was used to clip the imagery to the area of interest and calculate NDVI for each image scene.

**Table 1.** Comparison of UAV, airplane, and satellite imagery system resolutions.

| | UAV<br>Quantix Mapper UAV | Airplane<br>Ceres Aerial Imagery | Cube Satellite<br>PlanetScope |
|---|---|---|---|
| Spectral Resolution | 4 bands<br>Blue (458 nm)<br>Green (569 nm)<br>Red (619 nm)<br>NIR (840 nm) | 4 bands<br>Green (550 nm)<br>Red (670 nm)<br>Red-Edge (717 nm)<br>NIR (800 nm) | 4 bands<br>Blue (455 - 515 nm)<br>Green (500 - 590nm)<br>Red (590 - 670 nm)<br>NIR (780-760 nm) |
| Spatial Resolution | 0.05 m | 0.8 m | 3 m |
| Temporal Resolution | As Necessary | As Necessary | Daily |

Field management and in-season N recommendations

Starting with pre-plant urea fertilizer treatments, in-field operations were summarized per virtual grid using as-applied files provided by the grower or co-op applicator to correctly estimate the amount of fertilizer product applied. For each remote sensing platform, NDVI was calculated using red and near-infrared spectral bands and zonal statistics in QGIS were used to calculate the mean grid NDVI value. Imagery was clipped to remove unrepresentative regions such as weed infestations and unplanted drainage areas.

Response curve modeling was undertaken in Python (version 3.7) using JupyterLab (Kluyver et al., 2016) modules. Response curve fitting was undertaken using the *pandas* (McKinney, 2010) and *Matplotlib* (Hunter, 2007) libraries. The strategy to prescribe in-season N application involved selecting the highest performing pre-plant N rate +/- 30% of the FNR. If the 0 FNR pre-plant rate showed no NDVI difference or outperformed the higher N rates, the 70% FNR was selected as the ONR. In the case that two or more N rates possess the same mean NDVI value, the lowest rate with similar NDVI was selected as the ONR.

Timing of imagery and in-season application

Due to weather and machinery constraints, in-season management and imagery collection timing varied between fields. In the case of F1, the focal time for imaging and side-dress application was between July 11-17, 2019 (Table 2). Due to clouds obscuring field visibility at F2 in early July, PlanetScope imagery was only available for five days prior to the target imagery date. Conversely, images for F3 were focused earlier around June 16, 2020.

**Table 2.** Flight dates for different remote sensing platforms targeted at V8 corn growth stage in each field. Ceres Imaging image was not collected for F3.

| | Remote Sensing Platforms | | |
|---|---|---|---|
| Field | *PlanetScope* | *Ceres Imaging* | *Quantix Mapper* |
| F1 | 7/17/2019 | 7/11/2019 | 7/16/2019 |
| F2 | 6/27/2020 | 7/02/2020 | 7/02/2020 |
| F3 | 6/17/2020 | --- | 6/16/2020 |

## Results

Estimation of optimal nitrogen rate using NDVI and yield responses

The calibration strip-based N recommendation strategy assumes that corn yield response to N rates can be estimated using early season NDVI responses . Using the four check blocks implemented in each field experiment, in-season NDVI responses were compared to final grain yield responses. F1 displayed a close relationship between in-season NDVI and yield responses to N (Figure 1a), with approximately 100 kg $ha^{-1}$ maximizing grain yield. Unfortunately, several of the check blocks were accidentally applied with in-season N at F2; however, one of the check strips remained untreated which showed a similar yield trend to the early season NDVI response (Figure 1b). Though the NDVI response to N appeared to plateau after 100 kg $ha^{-1}$ of applied N, the yield continued to increase slightly from 150 to 220 kg $ha^{-1}$. F3 exhibited the greatest difference in relative trends between in-season NDVI and yield (Figure 1 c,d). In-season response curves predicted a limited response to N with low rates possessing equal or greater NDVI values compared to 100% FNR or the 130% FNR (Figure 1 c,d). However, the need for N was not reflected in the early season data for F3 since the N rates optimizing yield were higher than those projected based on NDVI responses (Figure 1 c,d). This was likely due to dry conditions early in the season that resulted in minimal N losses, which were followed by near optimal late season weather conditions that enabled the crop to take up all available N.

Comparison of different remote sensing platforms for N recommendation

Over the three site years, the remote sensing platforms performed comparably in estimating ONRs at V8 growth stage using the NDVI response curve method (Table 3). At F1, the PlanetScope and Quantix platform-based methods recommended similar ONRs with 90% of ONRs within 10 kg $ha^{-1}$ difference. However, the Ceres Imaging prescriptions at F1 were not as correlated to either PlanetScope or Quantix predictions. This could be explained by difference in imagery collection dates, July 11 versus July 16/17. Conversely at F2, the comparison of ONRs using the three remote sensing platforms indicated that 56-74% of blocks had less than 10 kg $ha^{-1}$ difference in ONR recommendation between any two platforms. Evaluating the mean absolute difference (MAD) in recommended rate at F2 showed a moderate difference between platforms, ranging from 18 to 29 kg $ha^{-1}$. Ceres Imaging data was not collected at F3 in 2020, but the comparison of PlanetScope and Quantix Mapper recommendations showed a strong relationship with 90% of grids within 10 kg $ha^{-1}$ recommendation and a mean absolute difference of around 9 kg $ha^{-1}$ per grid. Overall, these trends suggested that timing of imagery was likely a much greater factor in N rate prediction instead of spatial resolution of the remote sensing platforms.

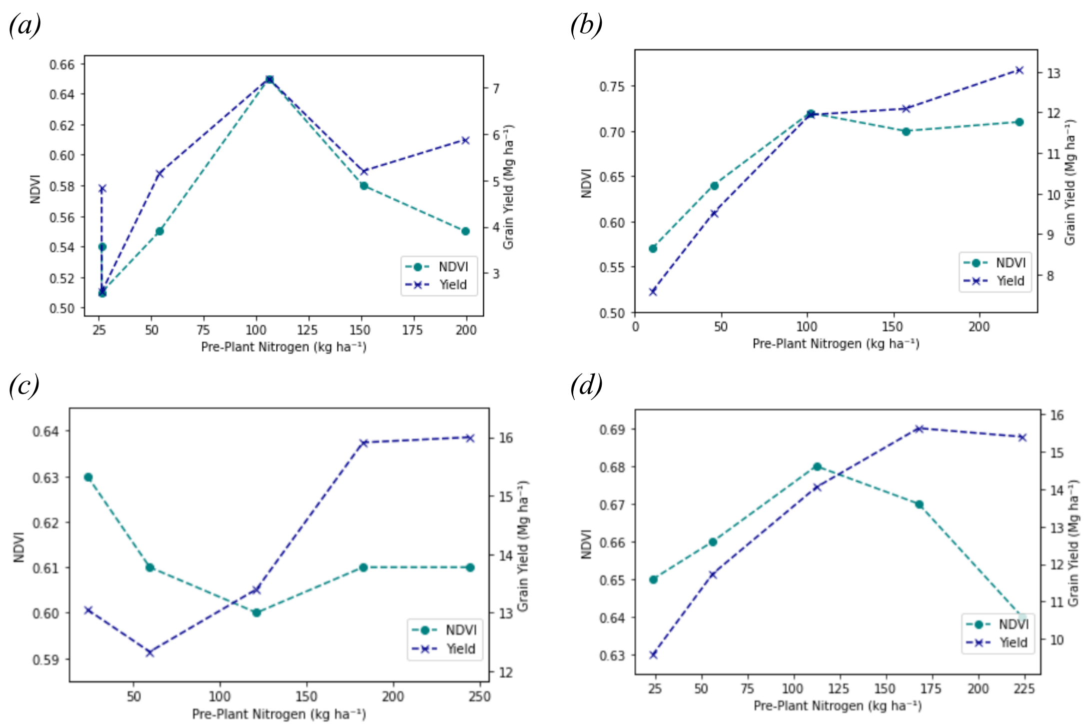


**Figure 1**. Comparison of corn yield and in-season normalized difference vegetation index (NDVI) responses based on PlanetScope satellite imagery collected prior to side-dress application at F1 (a), F2 (b), and F3 (c,d)

**Table 3.** Comparison of different Quantix Mapper, Ceres Imaging, and PlanetScope remote sensing platforms for optimal N rate (ONR) recommendations in different fields in terms of agreement (percentage of blocks having similar ONRs within 10 kg ha$^{-1}$ difference) and mean absolute difference (MAD).

| Field | PlanetScope/Quantix | | Quantix / Ceres | | Ceres/PlanetScope | |
|---|---|---|---|---|---|---|
| | Agreement (%) | MAD (kg ha$^{-1}$) | Agreement (%) | MAD (kg ha$^{-1}$) | Agreement (%) | MAD (kg ha$^{-1}$) |
| F1 | 90 | 8.7 | 57 | 29.3 | 67 | 20.6 |
| F2 | 68 | 22.4 | 56 | 28.9 | 74 | 18.5 |
| F3 | 90 | 8.7 | -- | -- | -- | -- |

Nitrogen use efficiency evaluation

Partial factor productivity (PFP) was calculated as the ratio of harvest grain and applied fertilizer using harvest data and the annual N rate to examine nitrogen use efficiency (NUE). Yield data was cleaned of outlier data using a cut-off of three standard deviations from the mean and adjusted to 15.5% grain moisture content. Average statistics were calculated from each field site using blocks that followed the suggested calibration strip-based method. This standardized format allowed the direct comparison between calibration strip blocks to determine the optimal rate. The PFP of F1 was higher (47-62 kg yield kg$^{-1}$ N) for calibration strip-based split-application grids while the solely pre-plant grids achieved considerably lower PFP (33-39 kg yield kg$^{-1}$ N). Corn yield was not significantly different between these two N management strategies in this field (5.9 Mg ha$^{-1}$ vs. 6.6 Mg ha$^{-1}$) (Figure 2 a,b).

The PFP for F2 grids ranged between 61-84 kg yield $kg^{-1}$ N, with the greatest NUE achieved by calibration strip-based in-season N application compared to all pre-plant N application treatments (Figure 2 c). There was not a statistical difference in PFP between in-season N management and 100% FNR areas. Corn yield at in-season N management grids was approximately 0.2 to 0.6 Mg $ha^{-1}$ lower compared to 100% FNR grids (Figure 2 d). The highest average yield was attained by the 130% FNR treatment, which on average was 0.3 Mg $ha^{-1}$ greater than 100% FNR treatment. Across the fields, F3 attained the highest overall PFP (65-124 kg yield $kg^{-1}$ N) and yield (13.6-15.3 Mg $ha^{-1}$) (Figure 2 e). The PFP of in-season N application grids were on average 40 to 60 kg yield $kg^{-1}$ N higher than solely pre-plant applied grids (Figure 2 e). Average yield was greatest for 100% and 130% FNR treatments (15 Mg $ha^{-1}$). However, only the in-season N management based on 0% FNR preplant N application treatment was statistically different from the other four N rates (Figure 2 f).

**Discussion**

Selecting an optimal N fertilizer rate has long been a challenge in corn production, which depends on farmer risk tolerance and constantly changing spatial variability in soil N supply versus temporal N demand from plants (Feinerman et al., 1990). This has led to many instances of over-application of N fertilizer, which has broad implications for farmer economic wellbeing, environmental sustainability, and human health (Keeler, et al, 2016). The results of this study demonstrated that in-season variable rate N applications could be guided using site-specific calibration strips and remote sensing at around V8 growth stage. F3 was very responsive to N fertilizers and achieved the highest corn yield among the three fields, due to very good weather conditions in 2020. Under such situations, the calibration strip-based N recommendation strategy could under-recommend N fertilizers. Early season weather conditions need to be incorporated into the decision-making process for future improvement. The three remote sensing platforms in general performed similarly, and the differences in ONR recommendations were mainly due to the difference in timing of remote sensing image collection, rather than difference in spatial resolution. The PlanetScope satellite remote sensing system has daily revisit time and 3 m spatial resolution, which makes it the most practical for large scale applications. However, either UAV or aerial remote sensing can be used for determining site-specific optimal N rates based on the calibration strip-based recommendation strategy, if the Planetscope images are unavailable or there is high cloud coverage. More studies are needed to further improve this in-season N management strategy by incorporating early season weather conditions and soil-landscape variables as well as site-specific in-season projected yield goals.

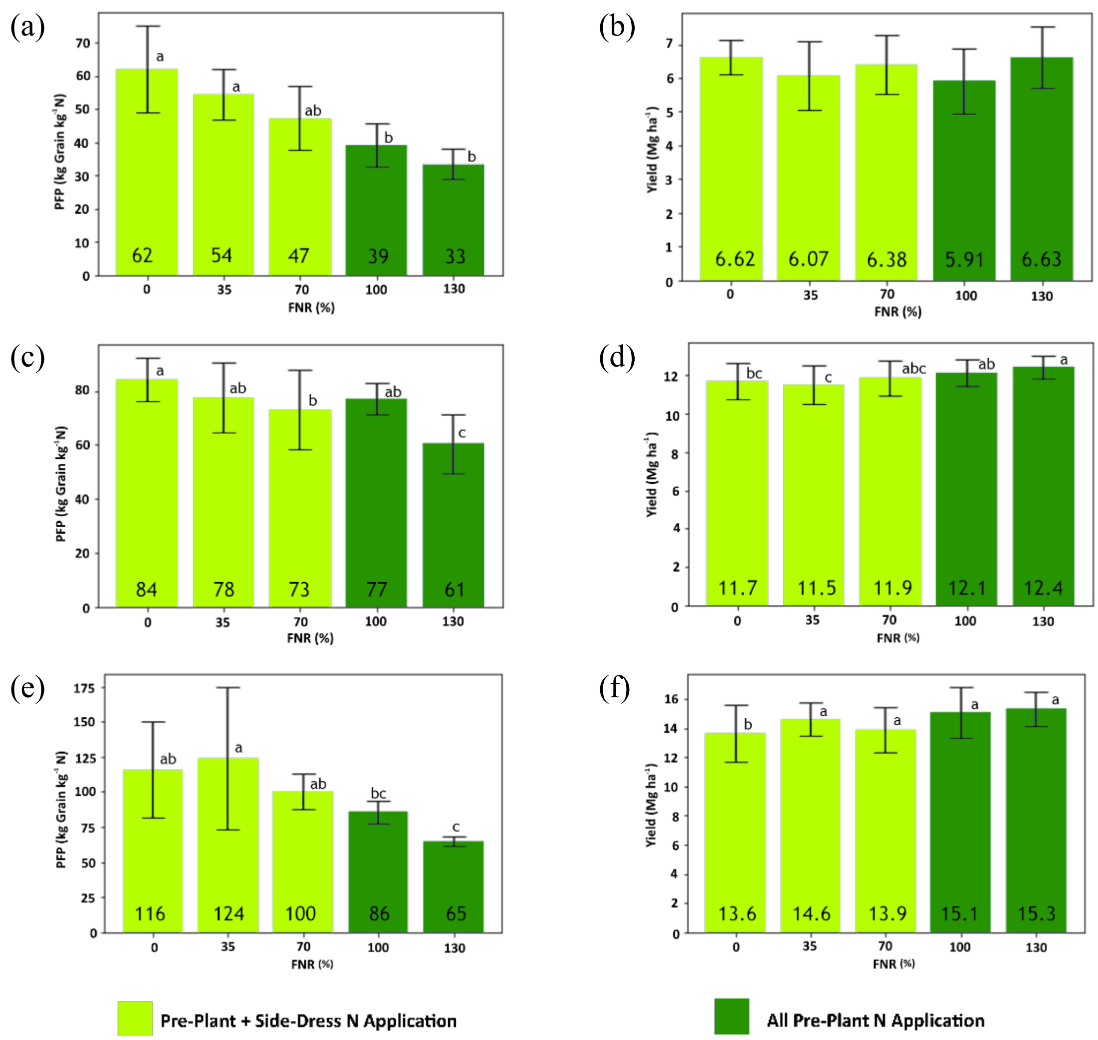


**Figure 2.** Mean partial factor productivity (PFP) and corn yield for treatments receiving 0%, 35%, and 70% farmer N rate (FNR) preplant N application and calibration strip-based variable rate side-dress N application compared with treatments of 100% FNR and 130% FNR preplant N application in F1 (a,b), F2 (c,d), and F3 (e,f). Standard deviation and statistical significance ($p<0.05$) are shown by error bars and different letters above the bars.

## Conclusion

In-season N recommendation for corn production is often fraught with uncertainty over how much N is needed by the growing crop for the rest of the growing season. This study demonstrated that in-season variable rate N applications could be guided using replicated calibration strips and remote sensing images collected around V8 growth stage. Overall, the difference between ONRs prescribed by each of the platforms was within 10 kg ha$^{-1}$ for approximately 60-90% of grids. The results indicated that this site-specific N recommendation strategy in general could increase NUE at all five field-years, while resulting in comparable yield at two of the three fields. Future research is needed to investigate how to incorporate soil landscape attributes and early season weather information to further improve this calibration strip-based in-season N recommendation strategy.

**References**


Cao, Q., Miao, Y., Feng, G., Gao, X., Liu, B., Liu, Y., et al. 2017. Improving nitrogen use efficiency with minimal environmental risks using an active canopy sensor in a wheat-maize cropping system. Field Crops Research, **214:** 365–372.

Feinerman, E., Choi, E. K., & Johnson, S. R. 1990. Uncertainty and split nitrogen application in corn production. American Journal of Agricultural Economics 72(4) 975-985.

Keeler, B. L., Gourevitch, J. D., Polasky, S., Isbell, F., Tessum, C. W., Hill, et al. 2016. The social costs of nitrogen. Science Advances, **2**(10): e1600219.

Kluyver, T., Ragan-Kelley, B., Pérez, F., Granger, B. E., Bussonnier, M., Frederic, J., et al. 2016. Jupyter Notebooks-a publishing format for reproducible computational workflows. In *ELPUB* (pp. 87-90). DOI:10.3233/978-1-61499-649-1-87

Hunter, J. D. 2007. Matplotlib: A 2D graphics environment. Computing in Science & Engineering, **9**(3): 90-95.

McKinney, W. 2010. Data structures for statistical computing in python. In Proceedings of the 9th Python in Science Conference, Austin, TX, USA, Vol. 445 pp. 51-56.

QGIS Development Team, 2020. QGIS Geographic Information System. Open-Source Geospatial Foundation. http://www.qgis.org

Raun, W. R., Solie, J. B., Taylor, R. K., Arnall, D. B., Mack, C. J., & Edmonds, D. E. 2008. Ramp calibration strip technology for determining midseason nitrogen rates in corn and wheat. Agronomy Journal, **100**(4):1088-1093.

Roberts, D.C., Brorsen, B.W., Taylor, R.K., Solie, J.B., Raun, W.R. 2011. Replicability of nitrogen recommendations from ramped calibration strips in winter wheat. Precision Agriculture, **12:** 653–665.

Robertson, G. P., & Vitousek, P. M. 2009. Nitrogen in agriculture: balancing the cost of an essential resource. Annual Review of Environment and Resources, 34: 97-125.

Scharf, P. C. 2001. Soil and plant tests to predict optimum nitrogen rates for corn. Journal of Plant Nutrition, **24**(6): 805-826.


## 2. Evaluating model-based strategies for in-season nitrogen management of maize using weather data fusion


**Summary:** One challenge in precision nitrogen (N) management is the uncertainty in future weather conditions at the time of decision-making. Crop growth models require a full season of weather data to run yield simulation, and the unknown weather data may be forecasted or substituted by historical data. The objectives of this study were to (1) develop a model-based in-season N recommendation strategy for maize (*Zea mays* L.) using weather data fusion; and (2) evaluate this strategy in comparison with farmers' N rate and regional optimal N rate in Northeast China. The CERES-Maize model was calibrated using data collected from field experiments conducted in 2015 and 2016, and validated using data from 2017. At two N decision dates - planting stage and V8 stage, the calibrated CERES-Maize model was used to predict

grain yield and plant N uptake by fusing current and historical weather data. Using this approach, the model simulated grain yield and plant N uptake well ($R^2$ = 0.85-0.89). Then in-season economic optimal N rate (EONR) was determined according to responses of simulated marginal return (based on predicted grain yield) to N rate at planting and V8 stages. About 83% of predicted EONR fell within 20% of measured values. Applying the model-based in-season EONR had the potential to increase marginal return by 120-183 $ ha$^{-1}$ and 0-83 $ ha$^{-1}$ and N use efficiency by 8-71% and 1-38% without affecting grain yield than applying farmers' N rate and regional optimal N rate, respectively. It is concluded that the CERES-Maize model is a valuable tool for simulating yield responses to N under different planting densities, soil types and weather conditions. The model-based in-season N recommendation strategy with weather data fusion can improve maize N use efficiency compared with current farmer practice and regional optimal management practice.

**Table 4**
The relationships between model simulated and measured maize leaf area index (LAI), aboveground biomass (AGB), grain yield (GY) and plant N uptake (PNU) based on results of calibration in 2015-2016 and evaluation in 2017 for black and aeolian sandy soils ("*" indicated $P \leq 0.05$).

| | | Calibration | | Evaluation | |
|---|---|---|---|---|---|
| | | Black soil | Aeolian sandy soil | Black soil | Aeolian sandy soil |
| LAI | $R^2$ | 0.65* | 0.80* | 0.86* | 0.82* |
| | RMSE | 0.87 | 0.57 | 0.49 | 0.39 |
| | RE | 28% | 25% | 20% | 20% |
| AGB | $R^2$ | 0.95* | 0.89* | 0.92* | 0.88* |
| | RMSE | 736.66 | 709.44 | 945.78 | 755.73 |
| | RE | 15% | 21% | 22% | 23% |
| GY | $R^2$ | 0.89* | 0.82* | 0.94* | 0.92* |
| | RMSE | 730.46 | 647.54 | 626.66 | 533.42 |
| | RE | 8% | 11% | 8% | 8% |
| PNU | $R^2$ | 0.96* | 0.84* | 0.93* | 0.92* |
| | RMSE | 11.40 | 21.41 | 18.62 | 15.48 |
| | RE | 6% | 16% | 12% | 12% |

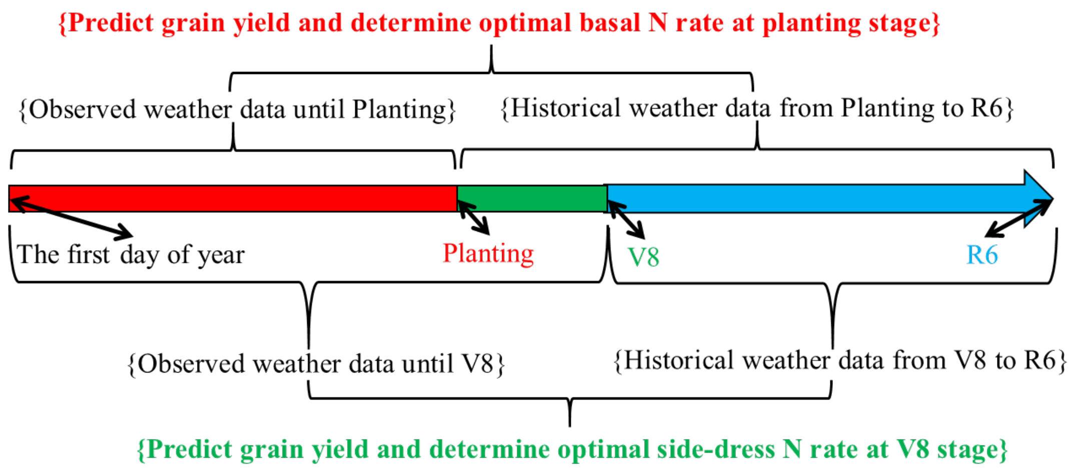


**Fig. 3.** Flow chart of the procedure to determine economic optimal N rate (basal N rate at planting stage and side-dress N rate at V8 stage) using crop growth model and weather data fusion. (Note: V8 - the eight-leaf stage; R6 - the maturity stage)

**Table 5**

The difference in N application rate, grain yield (GY), marginal return (MR), partial factor productivity (PFP), agronomic efficiency (AE), recovery N efficiency (RE) and N surplus (NS) among five different N management strategies across three years (2015-2017) in black soil and aeolian sandy soil fields.

| Soil type | Management | N rate (kg ha$^{-1}$) | GY (t ha$^{-1}$) | MR ($ ha$^{-1}$) | PFP (kg ha$^{-1}$) | AE (kg ha$^{-1}$) | RE (100%) | NS (kg ha$^{-1}$) |
|---|---|---|---|---|---|---|---|---|
| Black soil | CK | 0±0 | 6.00±2.03 | 1427±507 | | | | -71±22 |
| | FNR | 300±0 | 12.14±1.16 | 2693±288 | 40±4 | 20±9 | 62±9 | 44±8 |
| | RONR | 240±0 | 12.75±0.61 | 2894±152 | 53±3 | 28±10 | 66±11 | 11±19 |
| | EONR-A | 230±18 | 12.76±0.69 | 2906±180 | 56±6 | 29±11 | 67±11 | 4±28 |
| | EONR-H | 199±0 | 12.47±0.78 | 2861±195 | 63±4 | 33±12 | 71±11 | -13±18 |
| | EONR-I | 215±9 | 12.59±0.78 | 2877±189 | 59±1 | 31±11 | 69±10 | -5±14 |
| Aeolian sandy soil | CK | 0±0 | 3.54±0.98 | 828±246 | | | | -57±34 |
| | FNR | 300±0 | 8.01±1.19 | 1660±298 | 27±4 | 15±7 | 46±2 | 105±50 |
| | RONR | 240±0 | 7.90±1.48 | 1697±369 | 33±6 | 18±10 | 49±21 | 66±21 |
| | EONR-A | 159±9 | 8.41±1.21 | 1899±293 | 53±5 | 30±12 | 60±18 | 6±11 |
| | EONR-H | 177±0 | 7.99±1.19 | 1776±296 | 45±7 | 25±12 | 50±26 | 32±13 |
| | EONR-I | 175±9 | 8.00±1.19 | 1780±288 | 46±5 | 25±11 | 50±26 | 30±8 |

Note: FNR - farmers' N rate, RONR - regional optimal N rate, EONR-A - actual economic optimal N rate from field trials, EONR-H – simulated historical long-term average economic optimal N rate modeled by 30 years of weather data, EONR-I – simulated in-season economic optimal N rate modeled by weather data fusion. The number behind "±" is standard deviation calculated from three years' observations.

### 3. Corn Nitrogen Status Diagnosis with an Innovative Multi-Parameter Crop Circle Phenom Sensing System

**Summary:** Accurate and non-destructive in-season crop nitrogen (N) status diagnosis is important for the success of precision N management (PNM). Several active canopy sensors (ACS) with two or three spectral wavebands have been used for this purpose. The Crop Circle Phenom sensor is a new integrated multi-parameter proximal ACS system for in-field plant phenomics with the capability to measure reflectance, structural, and climatic attributes. The objective of this study was to evaluate this multi-parameter Crop Circle Phenom sensing system for in-season diagnosis of corn (Zea mays L.) N status across different soil drainage and tillage systems under variable N supply conditions. The four plant metrics used to approximate in-season N status consist of aboveground biomass (AGB), plant N concentration (PNC), plant N uptake (PNU), and N nutrition index (NNI). A field experiment was conducted in Wells, Minnesota during the 2018 and the 2019 growing seasons with a split-split plot design replicated four times with soil drainage (drained and undrained) as main block, tillage (conventional, no-till, and strip-till) as split plot, and pre-plant N (PPN) rate (0 to 225 in 45 kg ha−1 increment) as the split-split plot. Crop Circle Phenom measurements alongside destructive whole plant samples were collected at V8 +/−1 growth stage. Proximal sensor metrics were used to construct regression models to estimate N status indicators using simple regression (SR) and eXtreme Gradient Boosting (XGB) models. The sensor derived indices tested included normalized difference vegetation index (NDVI), normalized difference red edge (NDRE), estimated canopy chlorophyll content (eCCC), estimated leaf area index (eLAI), ratio vegetation index (RVI), canopy chlorophyll content index (CCCI), fractional photosynthetically active radiation (fPAR), and canopy and air temperature difference (ΔTemp). Management practices such as drainage, tillage, and PPN rate were also included to determine the potential improvement in corn N status diagnosis. Three of the four replicated drained and undrained blocks were randomly selected as training data, and the remaining drained and undrained blocks were used as testing data. The results indicated that SR modeling using NDVI would be sufficient for estimating AGB compared to more complex machine learning methods. Conversely, PNC, PNU, and NNI all benefitted from XGB modeling based on multiple inputs. Among different approaches of XGB modeling, combining management information and Crop Circle Phenom measurements together increased model performance for predicting each of the four plant N metrics compared with solely using sensing data. The PPN rate was the most important management metric for all models compared to drainage and tillage information. Combining Crop Circle Phenom sensor parameters and management information is a promising strategy for in-season diagnosis of corn N status. More studies are needed to further evaluate this new integrated sensing system under diverse on-farm conditions and to test other machine learning models.


**Figure 4.** Wells research site experimental design with four replicates of block resolution drainage treatments and sub-plot tillage and sub-sub plot pre-plant N treatments. Green plots signify pre-plant N treatments while purple plots are timing treatments outside the realm of this study. NT, ST, and CT stand for no-till, strip-tillage, and conventional-tillage, respectively. The numbers for the pre-plant N treatment plots indicate the N rates (kg ha$^{-1}$).

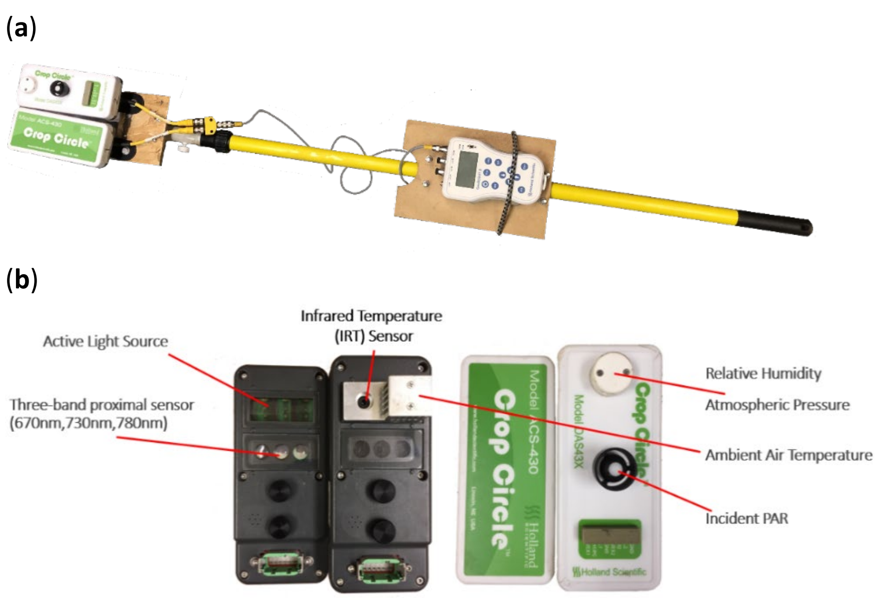


**Figure 5.** Crop Circle Phenom sensor (**a**) custom assembly with extendable pole and (**b**) close up view of ACS-430 and DAS43X sensor components.

**Table 6.** Corn N status diagnosis accuracy based on NNI prediction using SR and XGB regression results. Model precision was assessed using areal agreement (%) and kappa statistics (NNI<0.95 = deficient, 0.95<NNI<1.05 = optimum, NNI>1.05 surplus).

| | Areal Agreement (%) | | | | kappa Statistics |
|---|---|---|---|---|---|
| | Deficient (n = 37) | Optimum (n = 4) | Surplus (n = 26) | Overall (n = 67) | |
| NDRE | **70** | **25** | 23 | 49 | 0.22 |
| CCCI | 62 | 50 | 42 | 54 | 0.26 |
| XGB NDVI+NDRE | 70 | 0 | 50 | 58 | 0.31 |
| XGB All Phenom Metrics | 68 | 25 | 46 | 57 | 0.29 |
| XGB Phenom + Management | 68 | 50 | 81 | 72 | 0.54 |

## Implications for On-Farm Applications

Proximal sensing systems are beneficial for on-farm use because they require minimal training to collect data and fewer processing resources than aerial or satellite imagery. The Crop Circle Phenom sensor system is designed to be mounted on a vehicle or tractor, which makes it more difficult to be carried by hand for small plot research. To deploy it in small plot experiments, a custom pole was constructed to mount the two sensors and the GeoScout data logger. Another difference compared to similar proximal sensors is the Phenom requires an external 12 volt battery to power its active sensor light for calculating reflectance. Although the Crop Circle Phenom requires modifications for small plot research, adapting the sensor system for commercial field applications would be much easier because the mounting hardware and the electrical wiring were designed for use on a field implement. This ease of use for commercial applications is also due to its GPS connectivity and ability to quickly swap out the sensor across a range of field implements from sprayers to fertilizer spreaders, which enables whole field resolution readings to be collected throughout the growing season.

Another way in which the Crop Circle Phenom can set itself apart as a proximal sensing system is through its multi-parameter spectral, environmental, and physiological metrics. Utilizing biophysical relationships between spectral features and temperature, the Crop Circle Phenom can be used to estimate ΔTemp and fPAR. Although utilized in this study to investigate N status, these metrics have the potential to differentiate various stress factors such as water status and pathological issues. However, both these management considerations were outside the scope of this research and should be investigated in the future.

The PPN information was an important factor to use with crop sensor data for in-season N status prediction and diagnosis. Such data can be easily obtained from as-applied maps and should be included in in-season N status diagnosis, especially when variable rate PPN is applied.

**4. Corn Nitrogen Nutrition Index Prediction Improved by Integrating Genetic, Environmental, and Management Factors with Active Canopy Sensing Using Machine Learning**

**Abstract:** Accurate nitrogen (N) diagnosis early in the growing season across diverse soil, weather, and management conditions is challenging. Strategies using multi-source data are hypothesized to perform significantly better than approaches using crop sensing information alone. The objective of this study was to evaluate, across diverse environments, the potential for integrating genetic (e.g., comparative relative maturity and growing degree units to key developmental growth stages), environmental (e.g., soil and weather), and management (e.g., seeding rate, irrigation, previous crop, and preplant N rate) information with active canopy sensor data for improved corn N nutrition index (NNI) prediction using machine learning methods. Thirteen site-year corn (*Zea mays* L.) N rate experiments involving eight N treatments conducted in four US Midwest states in 2015 and 2016 were used for this study. A proximal RapidSCAN CS-45 active canopy sensor was used to collect corn canopy reflectance data around the V9 developmental growth stage. The utility of vegetation indices and ancillary data for predicting corn aboveground biomass, plant N concentration, plant N uptake, and NNI was evaluated using singular variable regression and machine learning methods. The results indicated that when the genetic, environmental, and management data were used together with the active canopy sensor data, corn N status indicators could be more reliably predicted either using support vector regression ($R^2$ = 0.74–0.90 for prediction) or random forest regression models ($R^2$ = 0.84–0.93 for prediction), as compared with using the best-performing single vegetation index or using a normalized difference vegetation index (NDVI) and normalized difference red edge (NDRE) together ($R^2 < 0.30$). The N diagnostic accuracy based on the NNI was 87% using the data fusion approach with random forest regression (kappa statistic = 0.75), which was better than the result of a support vector regression model using the same inputs. The NDRE index was consistently ranked as the most important variable for predicting all the four corn N status indicators, followed by the preplant N rate. It is concluded that incorporating genetic, environmental, and management information with canopy sensing data can significantly improve in-season corn N status prediction and diagnosis across diverse soil and weather conditions.

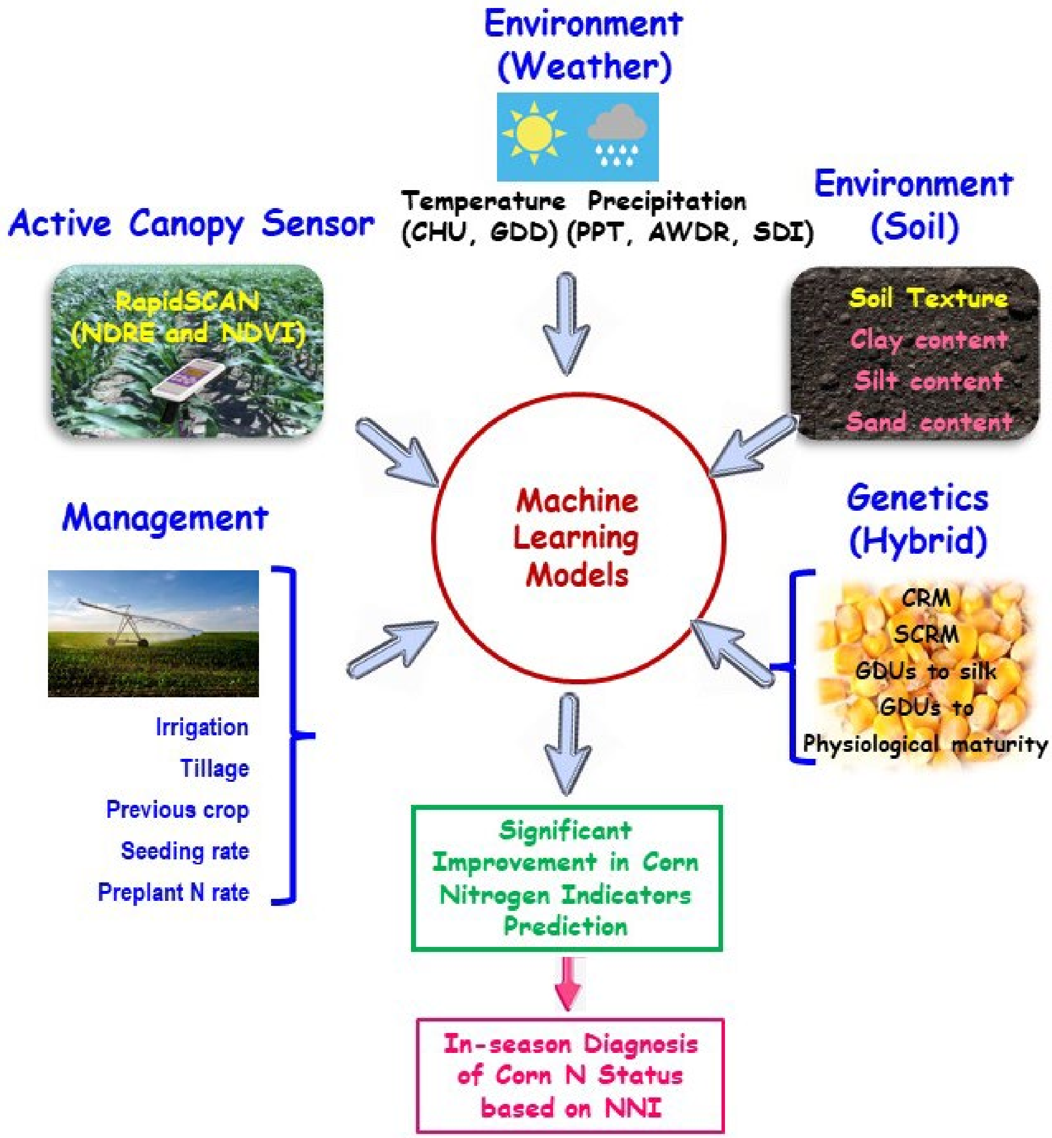


**Figure 6.** Illustration of the integration of genetics, environmental (soil and weather) and management variables with active canopy sensor data using machine learning models for in-season nitrogen nutrition index prediction and corn N status diagnosis.

**5. Develop and evaluate a remote sensing and machine learning model-based (RS-ML) PNM technology**

The RS-ML PNM technology is a combination of remote sensing data and machine learning algorithms to develop a NDVI prediction model using field specific characteristics. Initially, 12 different data sets were included (yield trend, yield stability, elevation, slope, aspect, curvature, topographic wetness index (TWI), clay content, organic matter, cation exchange capacity (CEC), pH, brightness index (BI)) in the NDVI prediction model. All data layers were converted to a 3 m grid to match with PlanetScope-derived NDVI spatial resolution. Data from the entire field was used for model development.

Based on the analysis we performed, the random forest model performed the best, and was selected, average grid NDVI was predicted by inputting different simulated total N rates from 0 to 300 in 20 lb increments while all other features remained the same. A curve was fitted to plot predicted NDVI and simulated total N rate and optimal N rate was selected based on response curve in similar manner to calibration strip approach. Prescribed sidedress N rate was defined as the difference between optimal N rate and total N rate that had been already applied to each grid. The determination of random forest-based optimal N rates for a grid is illustrated in Fig. 7.

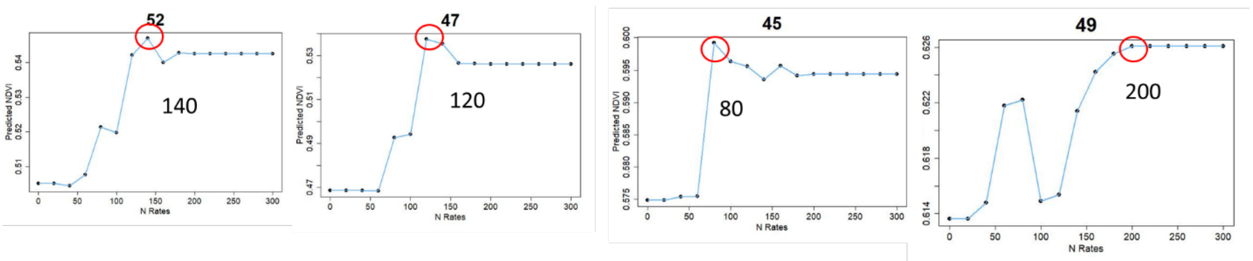


**Figure 7.** Illustration of determination of optimal N rates for each grid based on the random forest machine learning model.

**6. Identification of Key variables influencing yield spatial trend and temporal stability**

Yield variability in a field is driven by more than one factor. In addition to crop response to varying nitrogen rates, there are field intrinsic soil and landscape characteristics that limit yield potential in different areas of a field. In light of the results observed, machine learning algorithms were used to identify key factors affecting yield spatial trend and yield temporal stability for field B. To identify features that were relevant for the models, Boruta algorithm was used for feature selection (Figure 8). The algorithm uses a random forest classifier to set a mean threshold value that will serve as a reference to classify feature importance. Features that show importance value higher than the Shadow mean are deemed important, and their importance increases with higher values. Once all features initially used were deemed important for the model, different models were tested by excluding features that were highly correlated to each other. Data was divided into training, validation and test (70, 20 and 10%, respectively). Three ML algorithms were tested (support vector machine (SVM), random forest (RF), and XGBoost). The best prediction model was selected based on the highest $R^2$ and lowest error for training, validation and test sets (Table 7).

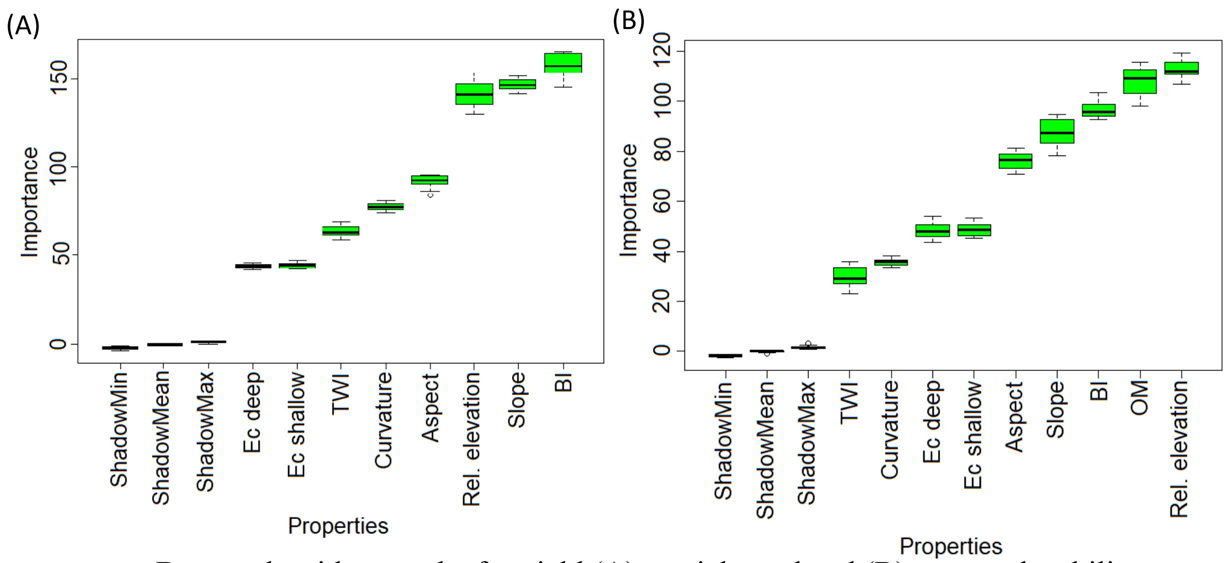


**Figure 8**. Boruta algorithm results for yield (A) spatial trend and (B) temporal stability feature selection in field B.

Although all properties were deemed important for predicting both yield spatial trend and temporal stability, the best performing models did not use all variables. The EC deep and the topographic wetness index (TWI) variables were excluded from both models due to data redundance. Curvature data were also excluded from the yield temporal stability prediction model. When comparing the machine learning algorithms used, random forest outperformed the SVM and the XGBoost for both prediction models. The random forest model for yield spatial trend prediction had an $R^2$ of 0.78, 0.79 and 0.78 and errors of 4.96, 4.99, and 4.96 for validation, training, and test sets, respectively. The best performing model for the yield temporal stability was random forest with $R^2$ of 0.69, 0.71, and 0.72, and errors of 2.88, 2.95 and 2.91 for validation, training, and test sets, respectively.

**Table 7.** Machine learning models training, validation and test results using shallow soil electrical conductivity (EC shallow), EC deep, curvature, organic matter, brightness index, TWI, relative elevation, slope and aspect data to predict yield spatial trend and temporal stability. Bold numbers indicate best performing model for each field.

| ML algorithm | Yield spatial trend | | | | | | Yield temporal stability | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Training | | Validation | | Test | | Training | | Validation | | Test | |
| | $R^2$ | RMSE | $R^2$ | RMSE | $R^2$ | RMSE | $R^2$ | RMSE | $R^2$ | RMSE | $R^2$ | RMSE |
| SVM[1] | 0.62 | 6.57 | 0.63 | 6.68 | 0.62 | 6.61 | 0.21 | 4.79 | 0.23 | 4.9 | 0.21 | 0.88 |
| RF[2] | **0.78** | **4.96** | **0.79** | **4.99** | **0.78** | **4.96** | **0.69** | **2.88** | **0.71** | **2.95** | **0.72** | **2.91** |
| XGBoost[3] | 0.72 | 5.70 | 0.73 | 5.66 | 0.73 | 5.59 | 0.56 | 3.49 | 0.6 | 3.41 | 0.61 | 3.35 |

[1]SVM: support vector machine.
[2]RF: random forest.
[3]XGBoost: extreme gradient boosting.

The identified important variables can be further used for management zone delineation. The important variables can be different for different fields, so suitable variables for management zone delineation will be field-specific. More research is needed to identify a common set of key variables that can be used for management zone delineation in different regions in Minnesota.

## 7. Management zone delineation and management zone-based N recommendation

Management zones were delineated based on yield spatial trend and yield stability map, BI, slope, and relative elevation maps resampled to a 5 m grid resolution (Figure 9). Total N rate applied and NDVI from each individual MZ were plotted, and response curves were developed in similar manner as the calibration strips approach. The identified optimal N rates in both MZs would be assigned to each grid within the MZ-based treatment strips based on which MZ overlapped with individual grids. However, due to high NDVI variability it was not possible to identify a trend in the NDVI response to different N rates. A split application method was used for sidedress N prescription for MZ-based strips instead. Total N applied for these grids were subtracted from the FNR and the difference in N was prescribed.

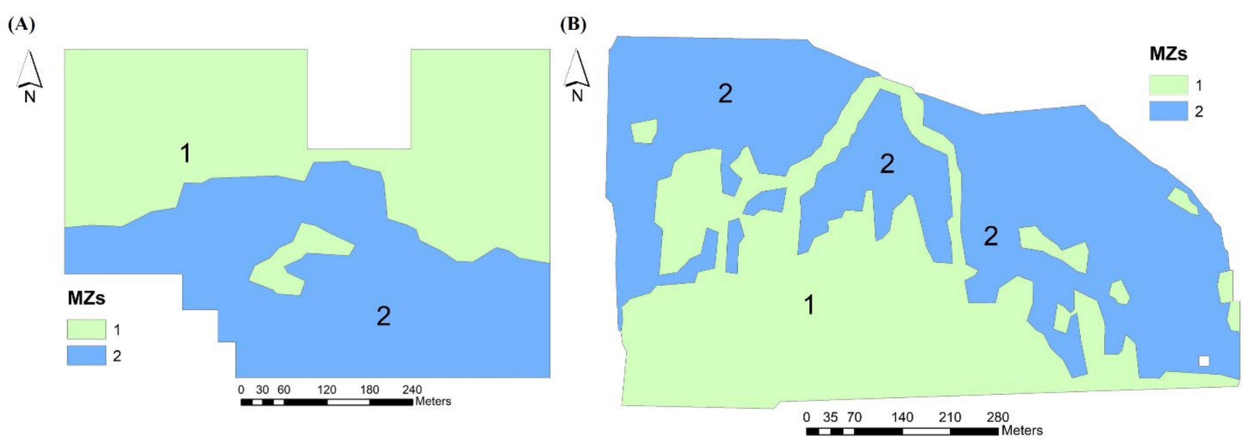


Figure 9. Fields A and B management zones delineated for the 2021 growing season.

## 8. On-farm evaluation of different PNM strategies

Two fields from the same two farms were selected in 2021 to evaluate different PNM strategies.

Tables 8 and 9 show the 2021 growing season monthly precipitation averages for both fields A and B located in the Maple Lake region and Traverse County, respectively, and compared to the 20-year averages for the same regions. In field A, the months of April, May, and July were the driest with total rainfall at least 63% lower than normal. Although total rainfall in June was 20% higher than the 20-year average, the precipitation events were not well distributed, which is an important factor to consider for sidedress N application timing. In a period of 25 days, from mid-May until June 10$^{th}$ the region received less than an inch of rain. This dry period was followed by a rainfall event of 2.3 inches and a subsequent second dry period of 10 days. In the end of June another extremely dry period was observed, which extended throughout the whole month of July.

In field B, although average season precipitation was only 6% below normal, rainfall distribution was irregular. Precipitation was above the normal average for the month of April followed by a dry period until July when sidedressing occurred. After sidedress application only the month of September showed lower precipitation. The unusually dry weather during the season presented a challenge to the sidedress N application timing. Despite UAN being less susceptible to volatilization than urea, the longer the fertilizer is on the soil without rain the higher the chances of losing N as ammonia.

**Table 8.** Monthly temperature averages for the 2021 growing season in Field A, MN.

| Month | 20-year average 2001-2021(in) | Measure rainfall (inches) | Rainfall departure from normal (%) |
|---|---|---|---|
| **April** | 3.0 | 1.09 | -63.7 |
| **May** | 4.2 | 1.22 | -71.0 |
| **June** | 4.0 | 4.81 | 20 |
| **July** | 4.2 | 1.08 | -74.3 |
| **Aug** | 3.6 | 3.0 | -16.7 |
| **Sept** | 4.0 | 3.69 | -7.8 |
| **Oct** | 3.1 | 1.88 | -39.4 |
| **Total** | 26 | 16.77 | **Avg.** -36.1 |

**Table 9.** Monthly temperature averages for the 2021 growing season in Field B, MN.

| Month | 20-year average 2001-2021(in) | Measure rainfall (inches) | Rainfall departure from normal (%) |
|---|---|---|---|
| **April** | 2.27 | 4.24 | 86.8 |
| **May** | 3.02 | 0.94 | -68.9 |
| **June** | 4.48 | 0.82 | -81.7 |
| **July** | 3.57 | 2.13 | -40.3 |
| **Aug** | 3.68 | 5.06 | 37.5 |
| **Sept** | 3.03 | 2.53 | -16.5 |
| **Oct** | 2.65 | 5.57 | 110.2 |
| **Total** | 22.7 | 21.3 | **Avg.** -6.2 |

The grain yield and net return/acre of each N management strategy for field A is summarized in Figure 10 and Table 10. The highest grain yield (202 bu/ac) was obtained in the 100% FNR treatment, in which all N was applied preplant. The 35% + CS treatment had the lowest grain yield of 171 bu/ac, while remaining treatments had a similar yield around 189 bu/ac. Despite the 30 bu/ac difference between the highest and lowest grain yields, the differences between treatments were not statistically significant. Net economic return was calculated using a partial budget analysis, which included only those costs that varied among treatments (N fertilizer and sideress N application costs) and revenue from grain yield. Nitrogen fertilizer costs were provided by the farmer. No statistical difference was seen between the treatments following the same trends as grain yield. The 100% FNR resulted in the highest net return, while the 35% FNR + CS resulted in the lowest.

**Table 10.** Economics of nitrogen treatments Field A in 2021.

| N application strategy | Total N rate | Grain yield | | Urea cost | UAN (32% N) cost | Net return | | Profit rank |
|---|---|---|---|---|---|---|---|---|
| | --lb/ac-- | --bu/ac-- | * | --------------$/ac-------------- | | | * | |
| **100% FNR[1]** | 144 | **202** | *a* | $49.96 | $0.00 | **$1,159.00** | *a* | 1 |
| **130% FNR** | 181 | 187 | *a* | $63.73 | $0.00 | $1,060.00 | *a* | 6 |
| **35% FNR + 65% FNR** | 150 | 189 | *a* | $17.79 | $28.55 | $1,090.00 | *a* | 4 |
| **35% FNR + CS** | 142 | **171** | *a* | $17.42 | $24.78 | **$985.00** | *a* | 7 |
| **35% FNR + Granular** | 151 | 190 | *a* | $17.73 | $29.13 | $1,091.00 | *a* | 2 |
| **35% FNR + RS-ML** | 146 | 189 | *a* | $17.07 | $28.21 | $1,087.00 | *a* | 5 |
| **70% FNR + CS** | 131 | 189 | *a* | $33.07 | $9.56 | $1,090.00 | *a* | 3 |

*Treatment yields that do not share the same letter are statistically different at a 90% confidence level.
[1]FNR: Farmer normal rate (150 N lb/ac)
Corn price: $6.00; Urea cost: $390.00/ton; UAN (32% N) cost: $225.00/ton; Y-Drop application cost: $8/ac (it is included as a reference, but it was not used in the net return calculation).

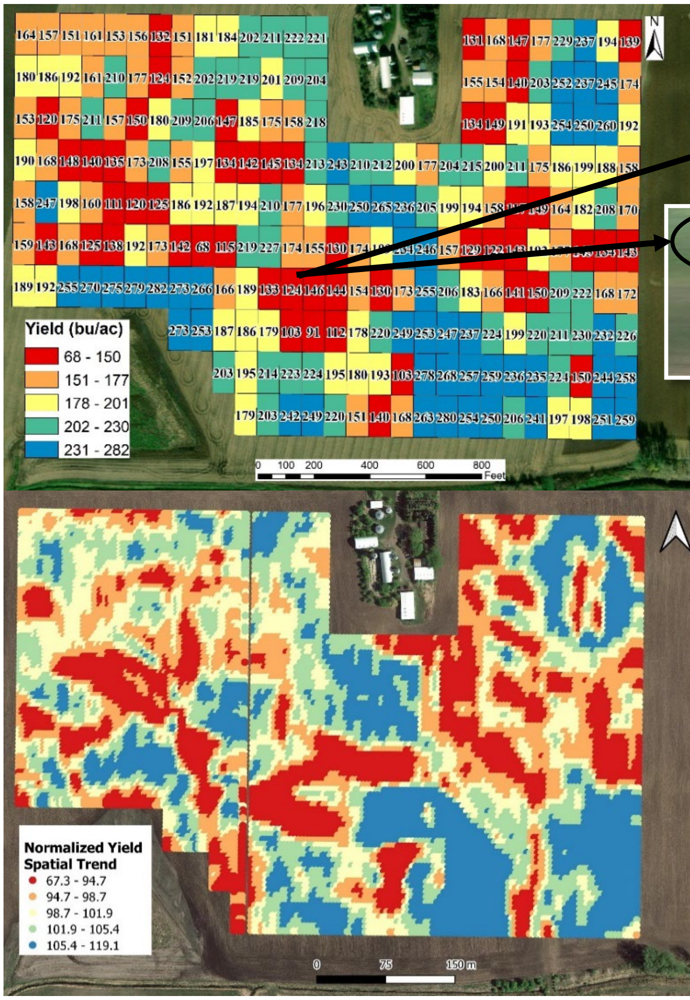


**Figure 10**. Field A 2021 plot yield (bu/ac) averages map and normalized yield trend map comparison. Yield data was cleaned before averages were calculated. The yield trend map was created based on 7 years of historical yield maps.

Although the whole field analysis did not show significant differences, it is possible to observe a high yield variability within each strip (Figure 3) suggesting that factors other than N application rates, such as soil and landscape properties are determinant for final yield. Thus, yield response to different N application rates will also vary across the field. The highlighted area is an example of a zone that has a low yield potential due to high slope. In these areas, crop production is limited by soil intrinsic factors and potentially have a low response to varying N rates.

**Table 11.** Economics of nitrogen treatments in Field B in 2021.

| N application strategy | Total N rate | Grain yield | | Urea cost | UAN (28% N) cost | Net return | | Profit rank |
|---|---|---|---|---|---|---|---|---|
| | --lb/ac-- | --bu/ac-- | * | --------------$/ac-------------- | | | * | |
| 100% FNR[1] | 150 | 204 | ab | $99.60 | $0.00 | $971.00 | a | 3 |
| 130% FNR | 200 | 209 | a | $137.41 | $0.00 | $960.00 | a | 5 |
| 35% FNR + 65% FNR | 154 | 205 | ab | $46.03 | $49.79 | $978.00 | a | 1 |
| 35% FNR + CS | 148 | 201 | ab | $50.34 | $42.47 | $963.00 | a | 4 |
| 35% FNR + Granular | 145 | 203 | ab | $45.35 | $44.74 | $977.00 | a | 2 |
| 35% FNR + RS-ML | 153 | 199 | b | $41.77 | $52.68 | $950.00 | a | 6 |
| 70% FNR + CS | 154 | 205 | ab | $76.43 | $22.85 | $978.00 | a | 1 |

*Treatment yields that do not share the same letter are statistically different at the 0.1 level.
[1]FNR: Farmer normal rate (150 N lb/ac)
Corn price: $5.25; Urea cost: $0.35/lb; UAN (28% N) cost: $2/ga.

Table 11 and Figure 11 show the summarized grain yield and net return summary results for field B. Significant differences were observed between the 130% and the 35% + RS-ML treatments. The highest yield was obtained in the 130% FNR treatment. However, due to the high total N rate (200 lb N/ac) used to achieve this yield, the 130% FNR treatment had one of the lowest profits ($960/ac). The 35% + RS-ML treatment had the lowest grain yield and net profit among all treatments. The highest net return was observed for the split application strategies applying 35% FNR at preplant and 65% FNR at sidedress and the 70% FNR + CS resulting in a net profit of $978.00 per acre.

Overall, results from both fields indicate that major benefits from adopting a split application strategy are more subtle in dry seasons, since with low precipitation and low soil moisture there is a low risk of N loss by leaching or denitrification. In addition to the dryer season and irregular rainfall, field B suffered the effects of high-intensity rainfall events. Many areas of the field were affected, and plants were broken down or lodged, which likely negatively impacted the yield across the field.

Similar to field A, yield spatial variability within treatments was also observed in field B. The overall field analysis showed small differences in net return and yield among the N strategies. However, based on the spatial distribution of individual grid results, it is possible to identify areas with higher response to different N rates than others using the yield spatial trend map. To increase profit, different N management strategies should be used in areas that are more responsive to varying N rates and areas that the crop shows lower yield independently of the amount of N applied.

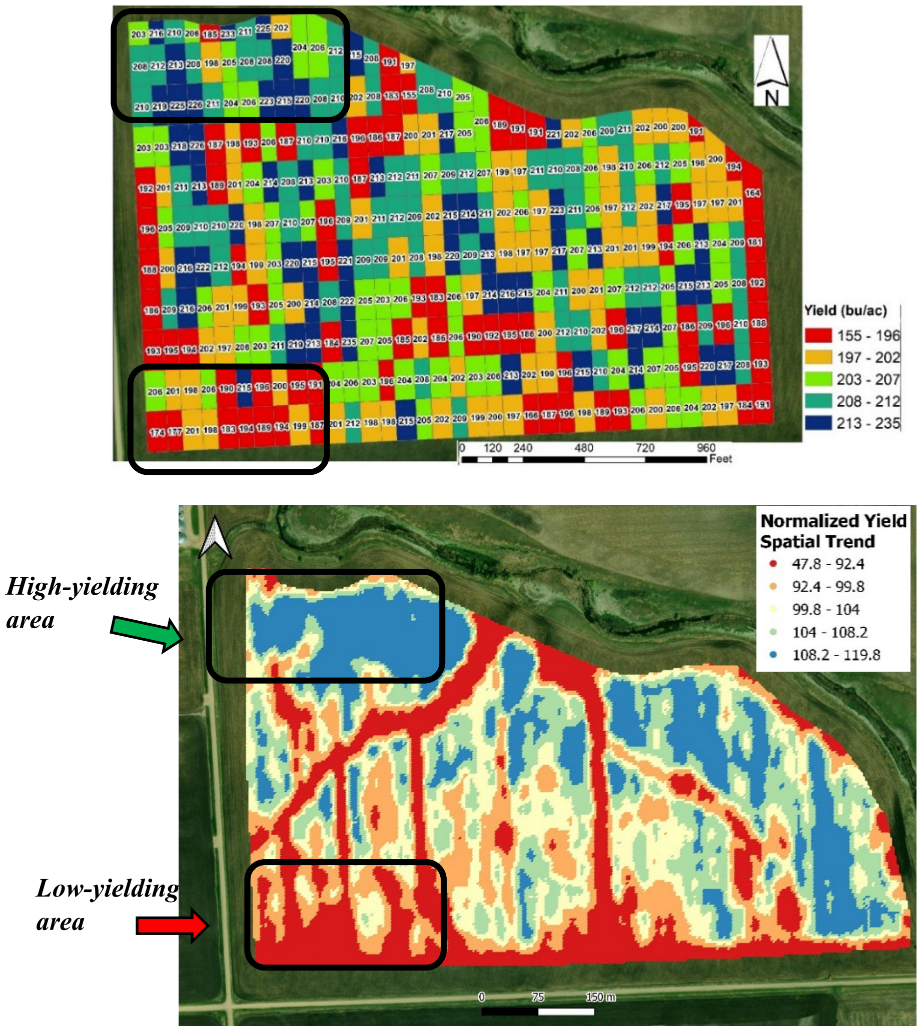


**Figure 11**. Field B 2021 plot yield (bu/ac) averages map and normalized yield trend map comparison. Yield data was cleaned before averages were calculated. The yield trend map was created based on 7 years of historical yield maps from 2014-2020.

## Limitations and Future Research

The current analysis results are based on the assumption that the within-transect variability is minimal. However, one transect covered 7 grids in this study and there were obvious soil and landscape as well as yield potential variabilities within transects. Therefore, current results can contain errors and bias.  New machine learning analysis methods are being studied to include soil landscape variables as well as yield potential information to better evaluate the performance of different N management strategies and technologies, and will reported later.

## OUTREACH

**1. Farmer Meetings:** We organized an annual meeting inviting all the farmers and consultants involved in on-farm N trials to share what we have done, what we learned and how we can help the farmers to improve their management in  Jan., 2020, Dec. 2020, and Jan. 2022. The Jan. meeting in 2020 was held in University of Minnesota (Figure 12), while the other two meetings were help on-line due to the pandemic (Figure 13 and Figure 14). The farmers really enjoyed this meeting and would love to continue to work with us in 2020.

Fig. 12. Project meeting involving cooperative farmers, crop consultant, researchers and graduate students on Jan. 7, 2020.

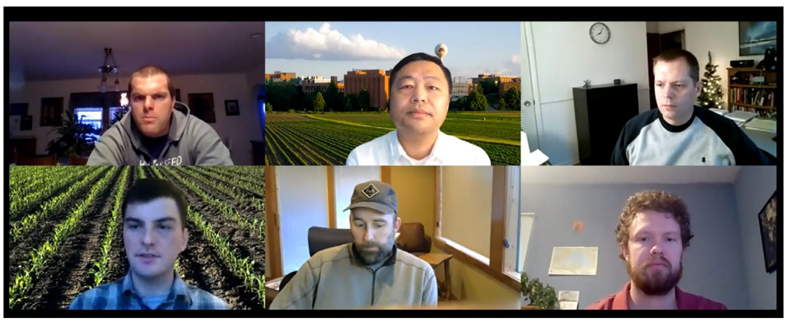

Fig. 13. Project meeting involving cooperative farmers, crop consultant, researchers and graduate student on Dec. 18, 2020.

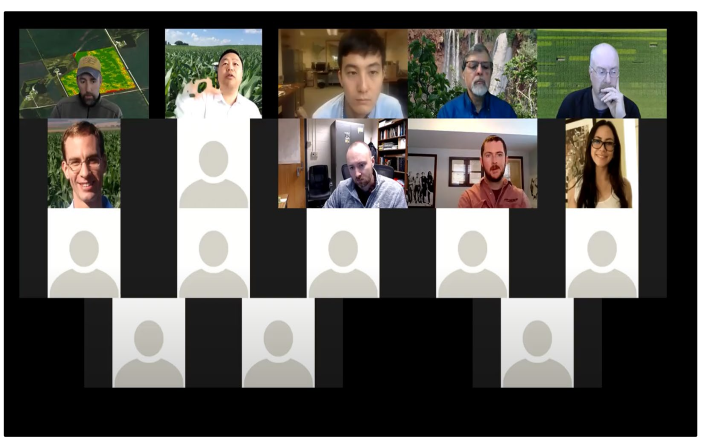

Fig. 14. Project meeting involving cooperative farmers, crop consultant, researchers and graduate student on Jan. 11, 2022.

2. **Blog postings**

Miao, Y. (2021). *On-farm precision ag research update: In-season site-specific side-dress nitrogen rate recommendations for corn*. Minnesota Crop News.

Miao, Y. (2020). *Minnesota and Indiana corn growers needed for on-farm precision nitrogen management research project*. Minnesota Crop News.

**3. Meeting Presentations**

Dr. Yuxin Miao, graduate student and postdocs involved in this project have presented results form this project at several different local, national and international meetings and conferences. The presentations are listed below.

Miao, Y. Improving Decision Making in Precision Nitrogen Management using Machine Learning. China-US Bilateral Forum on Precision Agriculture & China (Weifang) Modern Agriculture Forum (Virtual). Nov. 11, 2021.

Miao, Y. Improving Decision Making in Precision Agriculture Using Artificial Intelligence: Case Studies for Precision Nitrogen Management. At Cross Divisional Symposium "Artificial Intelligence in Soil and Environmental Sciences", ASA, CSSA, SSSA International Annual Meeting. (November, 2021). Invited.

Cummings, C., Miao, Y., Kang, S., Stueve, K. Developing a remote sensing and calibration strip-based in-season nitrogen management strategy for corn. 13th European Conference on Precision Agriculture, Budapast, Hungary (July 2021).

Miao, Y. Proximal and Remote Sensing-based Precision Nitrogen Management. 7th Annual Nitrogen: Minnesota's Grand Challenge and Compelling Opportunity Conference University of Minnesota Extension and the Minnesota Agricultural Water Resource Center. (February 9, 2021).

Miao, Y. Proximal and Remote Sensing Technologies for Corn Nitrogen and Water Stress Detection. 2021 Becker Irrigation and Nutrient management field day University Extension. (August 30, 2021).

Miao, Y. Precision Nitrogen Management for High Nitrogen Use Efficiency and Protection of the Environment. 47th Annual Hermiston Farm Fair Oregon State University. (December 3, 2020).

Miao, Y. Precision Agriculture for Food Security and Sustainable Development. MDA Non-Point Fertilizer Section Meeting MDA. (November 19, 2020).

Miao, Y. Development of Management Zones and the Use of Active/Passive Sensors in Crop and Crop Nutrient Site-specific Management. Advanced Crop Advisors Workshop North Dakota State University. (February 2020).

Cummings, C., Miao, Y., Fernandez, F. G., Paiao, G. D. Evaluating Crop Circle Phenom Active Canopy Sensor for Corn Nitrogen Status Diagnosis in Minnesota. Annual ASA-CSSA-SSSA Meeting ASA-CSSA-SSSA, San Antonio, Texas, United States. (November 12, 2019).

**4. Publications**

Li, D., Miao, Y., Ransom, C.J., Bean, G.M., Kitchen, N.R., Fernandez, F.G., Sawyer, J.E., Camberato, J.J., Carter, P.R., Ferguson, R.B., Franzen, D.W., Laboski, C.A.M., Nafziger, E.D., Shanahan, J.F. (2022). Corn nitrogen nutrition index prediction improved by integrating genetic, environmental, and management factors with active canopy sensing using machine learning. Remote Sensing 14(2), 394.

Cummings, C., Miao, Y., Paiao, G. D., Kang, S., & Fernandez, F. G. (2021). Corn Nitrogen Status Diagnosis with an Innovative Multi-Parameter Crop Circle Phenom Sensing System. Remote Sensing, 13(3), 401. doi: 10.3390/rs13030401

Cummings, C., Miao, Y. (Corresponding Author), Kang, S., & Stueve, K. (2021). Developing a remote sensing and calibration strip-based in-season nitrogen management strategy for corn. Precision agriculture'21 805--826. Wageningen Academic Publishers.

Wang, X., Miao, Y., Batchelor, W. D., Dong, R., & Kusnierek, K. (2021). Evaluating model-based strategies for in-season nitrogen management of maize using weather data fusion. Agricultural and Forestry Meteorology, 308-309, 108564.

Wang, X., Miao, Y., Dong, R., Zha, H., Xia, T., Chen, Z., . . . Li, M. (2021). Machine learning-based in-season nitrogen status diagnosis and side-dress nitrogen recommendation for corn. European Journal of Agronomy, 123(2), 126193.

Wang, X., Miao, Y. (Corresponding Author), Dong, R., Chen, Z., & Kusnierek, K. (2021). Improving in-season nitrogen status diagnosis using a three-band active canopy sensor and ancillary data with machine learning. Precision agriculture'21 451-457. Wageningen Academic Publishers.

Franzen, D., Miao, Y., Kitchen, N., Schepers, J., & Scharf, P. Health, Vigour and Disease Detection in Arable Crops. In Kerry, R. & Escola A. (Eds.) Sensing Approaches for Precision Agriculture. Springer, Cham, pp 159-193.

Dong, R., Miao, Y., Wang, X., Yuan, F., Kusnierek, K. (2022). Combining leaf fluorescence and active canopy reflectance sensing technologies to diagnose maize nitrogen status across growth stages. Precision Agriculture (Online first).

Dong, R., Miao, Y., Wang, X., Yuan, F., Kusnierek, K. (2021). Canopy fluorescence sensing for in-season maize nitrogen status diagnosis. Remote Sensing, 13(24), 5141.

Dong, R., Miao, Y., Wang, X., Chen, Z., & Yuan, F. (2021). Improving maize nitrogen nutrition index prediction using leaf fluorescence sensor combined with environmental and management variables. Field Crops Research, 269(15), 108180. doi:10.1016/j.fcr.2021.108180

Dong, R., Miao, Y., Wang, X., Chen, Z., Yuan, F., Zhang, W., & Li, H. (2020). Estimating Plant Nitrogen Concentration of Maize using a Leaf Fluorescence Sensor across Growth Stages. Remote Sensing, 12(7), 1139.