Final Report for AFREC & Minnesota Department of Agriculture

Pesticide & Fertilizer Management Division

AFREC R2023-9

FINAL REPORT

FOR THE PERIOD April 1, 2023 – March 31, 2024

SWIFT CONTRACT NUMBER: 225970**;** PURCHASE ORDER NUMBER: 3000045275

PROJECT RESCRIPTION: **Developing Guidelines for Variable Rate Nitrogen Management of Corn in Minnesota**

REPORT DUE DATE: **April 30, 2024**

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Progress in 2023

Objective 1: Identifying key factors influencing corn optimum N rates using deterministic cropping system models.

1) On-farm simulation and analysis:

The Elm Grove Family Farm in central Minnesota, Wright County (Figure 1, left). The selected field has a total area of 54 acres. The field is under corn and soybean rotations. The soils of the study field mainly consisted of a combination of Lester loam (Fine-loamy, mixed, superactive, mesic Mollic Hapludalfs), Angus loam (Fine-loamy, mixed, superactive, mesic Mollic Hapludalfs), and Glencoe clay loam (Fine-loamy, mixed, superactive, mesic Cumulic Endoaquolls) (Figure 1, right). The angus, cordova and glencoe soils are situated in a flat landscape under tile drainage. The Lester soil series that covers the central and southwestern portion of the field has undulating landscape with an average slope of 8%.

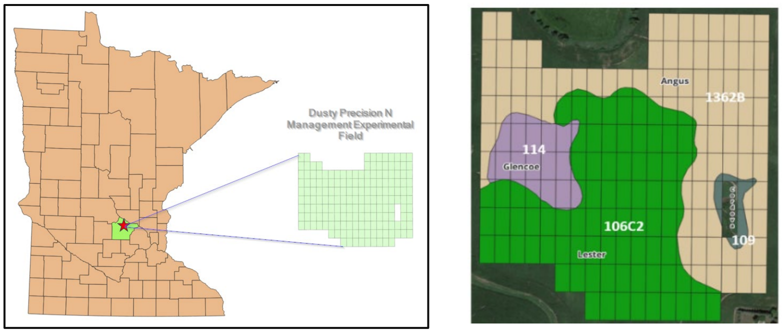


Figure 1. The location of the selected farm and field (left) and the soil distribution of the field.

Precision N management on-farm trials were conducted in the years 2020 and 2022. Both years had a dry growing season. The experimental site has 176 plots with 0.294 acres each, distributed across four soil types shown in figure 2.

Five combinations of treatments were applied across the plots: 0% Farmers N Rates (FNR), 35% FNR, 70%FNR, 100%FNR and 130%FNR in 2020.

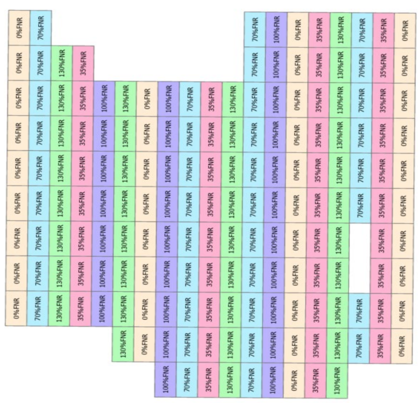


Figure 2. The treatments in each plot (grid) in 2020 in the study field.

The Erosion Productivity Impact Calculator (EPIC) model (Williams, 1995) was selected for this research study. EPIC has numerous advanced functions pertaining to water quality and CO_2 in global climate change. The model capability to accurately simulate the transport and fate of nutrients from fertilizer and manure applications has been put to the test. There are several field scale studies of crop land water and N balance using EPIC model. The effects of agronomic management practices on crop yield, crop growth and N uptake, and nitrate losses through tile drainage, leaching, runoff, denitrification, volatilization has been simulated in this modeling effort.

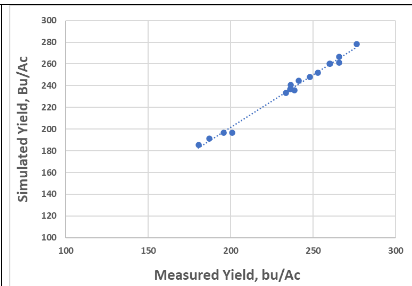
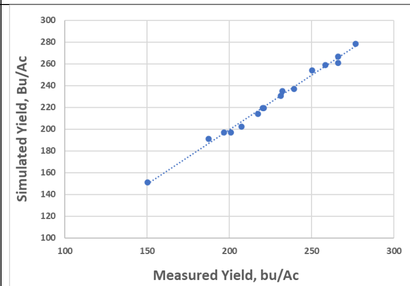
	100% FNR Treatment	Evaluation Stat
Calibration		NSE= 0.95 PBIAS = 0.37 RSR = 0.10
Validation		NSE= 0.94 PBIAS = 0.23 RSR = 0.09

Figure 3. Model calibration and validation under farmer normal nitrogen management.

2) Calibrating Crop Growth Modeling under Variable N and Irrigation Conditions:

To better simulate corn responses to N under different water supply conditions, the AFREC supported Irrigation x N experiments conducted in Becker and Westport are being used to calibrate DSSAT and APEX models to evaluate the potential of these models to simulate corn responses to N and irrigation under sandy soil conditions. The preliminary results of the DSSAT CERES-Maize model's performance for simulating corn yield after initial calibration in Becker is shown in Figure 4. After the final calibration is done, the models will be used to identify key factors influencing corn optimum N rates and understand how these factors will influence the optimum N rates.

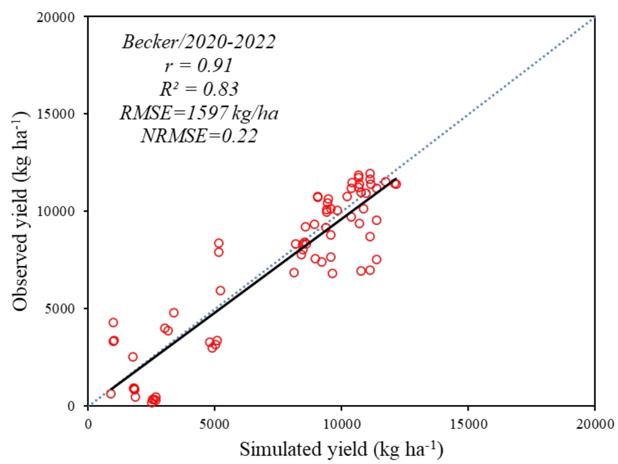


Figure 4. Relationship between observed corn yield and simulated yield for Becker irrigation x N experiments after initial calibration.

Objective 2. Identifying key factors influencing corn optimum N rates using machine learning models.

We have been compiling all the on-farm N trial data into a big database. The database has been completed based on on-farm trials conducted in 2021 and 2022. Machine learning analysis has been performed to identify the key factors influencing corn optimum N rates.

1) Development and validation of machine learning-based corn yield prediction model

The corn yield prediction model was developed using 2021-2022 on-farm trial data, and validated using ¼ of the data not used to develop the model, and the result was very promising (R^2=0.79) (Figure 5).

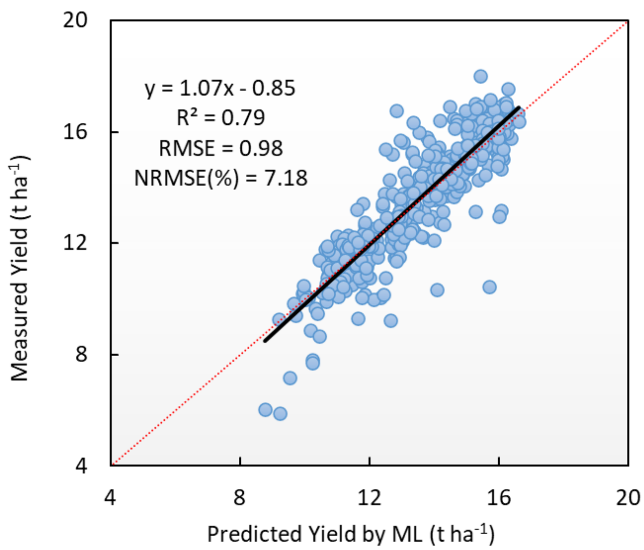


Figure 5. The validation result of corn yield prediction model developed using random forest algorithm.

2) Identification of key influencing variables

Based on the machine learning model, 15 important variables were identified and ranked. Elevation is the most important variable, followed by preplant N rate, sidedress N rate and plant population. Accumulated precipitation was the fifth important variable, followed by remote sensing-related variables (NDVI, soil brightness index and NDRE), then followed by topographic variables. Soil OM and pH were the 14th and 15th important variables (Table 1).

Table 1. Relative importance of environmental and management variables for corn yield prediction based on random forest machine learning model.

Rank	Category	Features	Importance
1	**Topography**	Elevation	**41.0%**
2	**Management**	Pre-plant N rate	**8.4%**
3	**Management**	Side-dressing N rate	**7.1%**
4	**Management**	Plant population	**7.1%**
5	**Weather**	Accumulated Precipitation	**5.7%**
6	**Remote sensing**	NDVI	**4.0%**
7	**Soil**	Soil Brightness Index	**3.9%**
8	**Remote sensing**	NDRE	**3.3%**
9	**Topography**	Tangential curvature	**1.5%**
10	**Topography**	Relative elevation	**1.5%**
11	**Topography**	Aspect	**1.2%**
12	**Management**	Seeds rate	**1.0%**
13	**Topography**	Topographic Wetness Index	**0.9%**
14	**Soil**	Organic matter_30-60cm	**0.8%**
15	**Soil**	pH_30-60cm	**0.8%**

3) Relationships between key soil variables and corn yield

Soil brightness index (SBI) is calculated using bare soil images (PlanetScope satellite), and it was negatively related to soil OM and soil moisture. It was negatively related to yield (Figure 6). It was the most important soil variable influencing corn yield. Soil silt content and bulk density were negatively correlated with yield, while sand, clay, soil water content, pH and SOM were all positively correlated with corn yield.

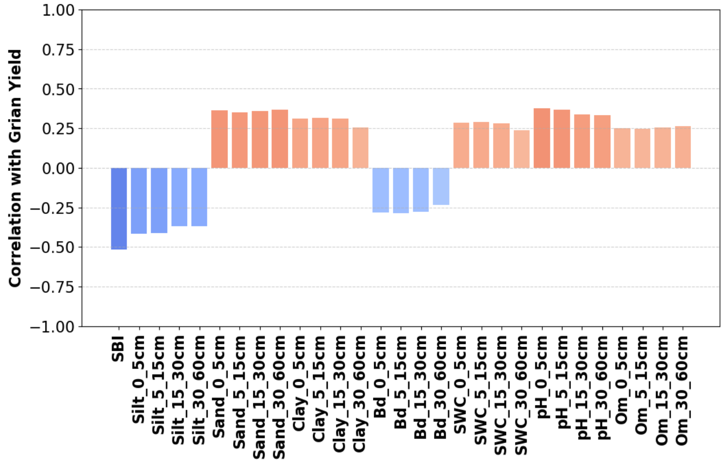


Figure 6. Relationships between corn yield and soil variables across site-years based on on-farm trials.

4) Relationships between topographic attributes and corn yield

Relative elevation was identified as the most important topographic attribute influencing corn yield, and the relationship was negative, with locations at higher relative elevation having lower yield (Figure 7). This is mainly related to soil moisture conditions, as 2021 and 2022 were quite dry. Terrain wetness index (TWI) is positively correlated with corn yield, as locations with high TWI will have higher soil moisture. All topographic attributes except TWI are negatively correlated with corn yield.

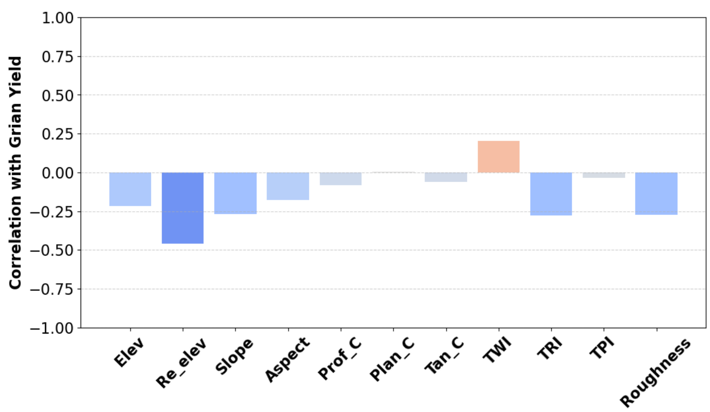


Figure 7. Relationships between corn yield and terrain attributes across site-years based on on-farm trials.

5) Relationships between weather variables and corn yield

Shannon diversity index (SDI) was the most important weather variable influencing corn yield. SDI is a variable indicating rainfall variability. A high SDI indicates more even distribution of rainfall, while a low SDI indicates less even distribution of rainfall. Accumulated precipitation (AccPPT) was the second most important weather variable and was positively correlated with corn yield. Accumulated growing degree days (AccGDD) was the third important weather variable and was positively correlated with corn yield (Figure 8).

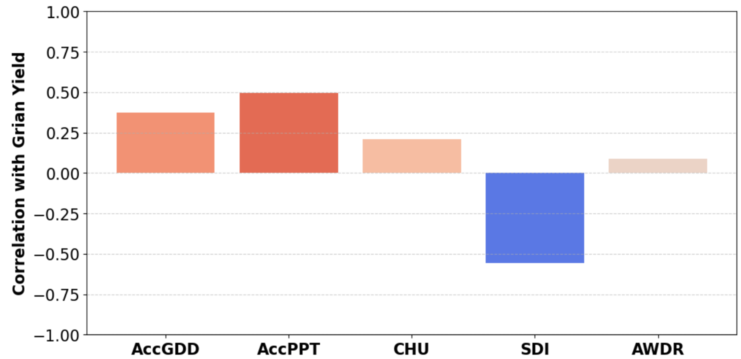


Figure 8. Relationships between corn yield and weather variables across site-years based on on-farm trials.

6) Relationships between management variables and corn yield

Seeding rate was the most important management variable influencing corn yield, with higher seeding rate producing higher corn yield. Basal N rate (preplant N rate) was more important than sidedress N rate (Figure 9).

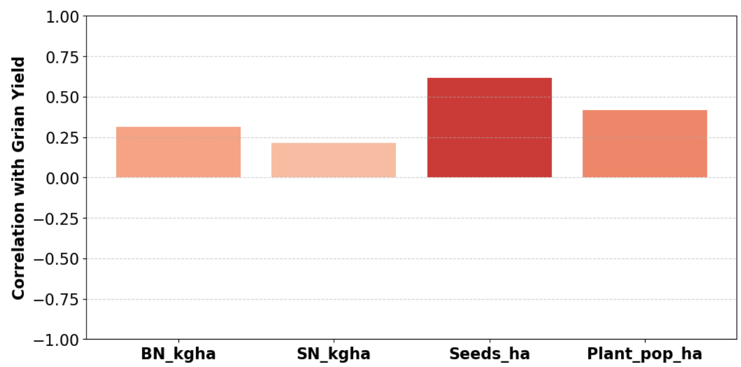


Figure 9. Relationships between corn yield and management variables across site-years based on on-farm trials.

7) Relationships between satellite remote sensing variables and corn yield

NDVI was most correlated with corn yield, followed by NDRE (Figure 10). This indicates that NDVI at V7-V9 is a good indicator of yield potential.

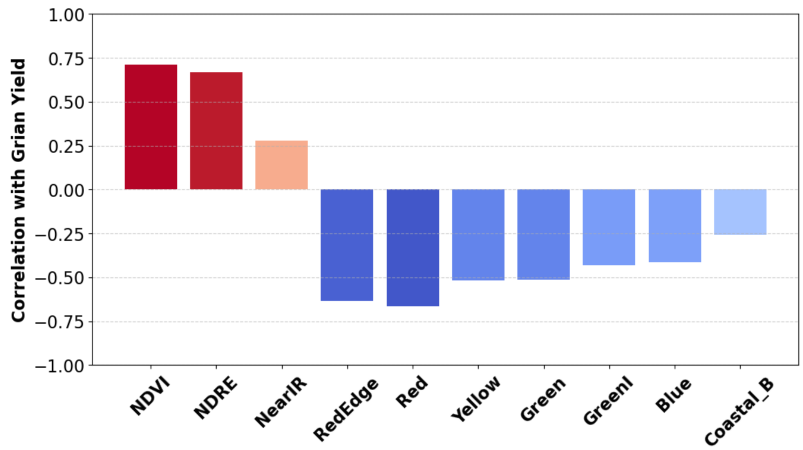


Figure 10. Relationships between corn yield and remote sensing variables across site-years based on on-farm trials.

8) 2023 field-specific key variables influencing corn yield

All the on-farm trials conducted in 2023 were analyzed, and the field-specific key factors influencing corn yield were identified (Figure 11-15). Relative elevation was identified as the top 1 important factor in 8 out of 13 fields, even more important than N rate. In 3 out of the remaining 5 fields, relative elevation was the second more important factor. Organic matter was identified as among the top 3 important factors in 7 out of 13 fields. Seeding rate was identified as among the top 3 important factors in 4 fields. Total N rate was identified as among the top 3 important factors in 7 out of 13 fields. Soil brightness index was identified among top 5 important factors in 7 out of 13 fields. Aspect was among the top 5 important factors in 5 out of 13 fields.

Efforts are being made to compile the database across on-farm trials and develop machine learning models to identify key factors across Minnesota corn fields.

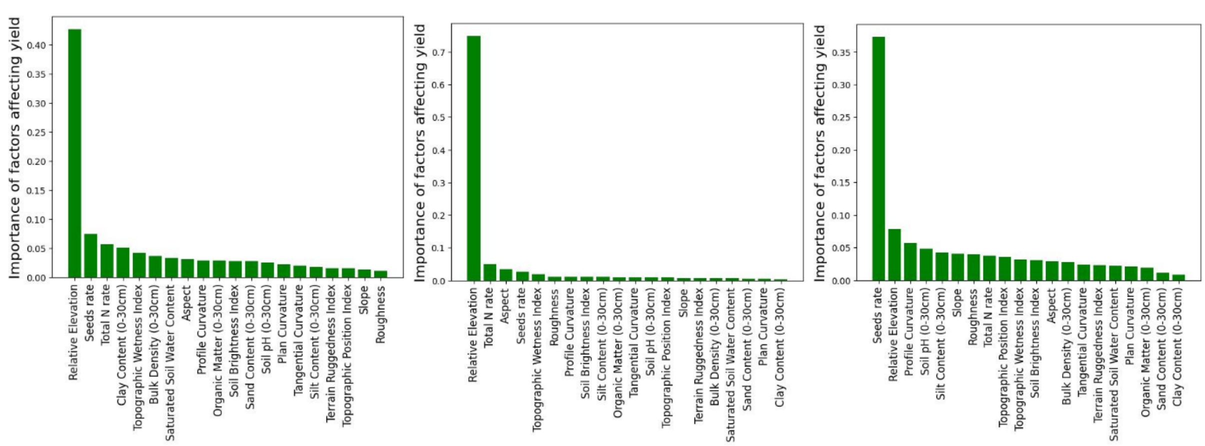


Figure 11. Key factors influencing corn yield identified using machine learning models in F1(left), F10(middle) and F13 (right).

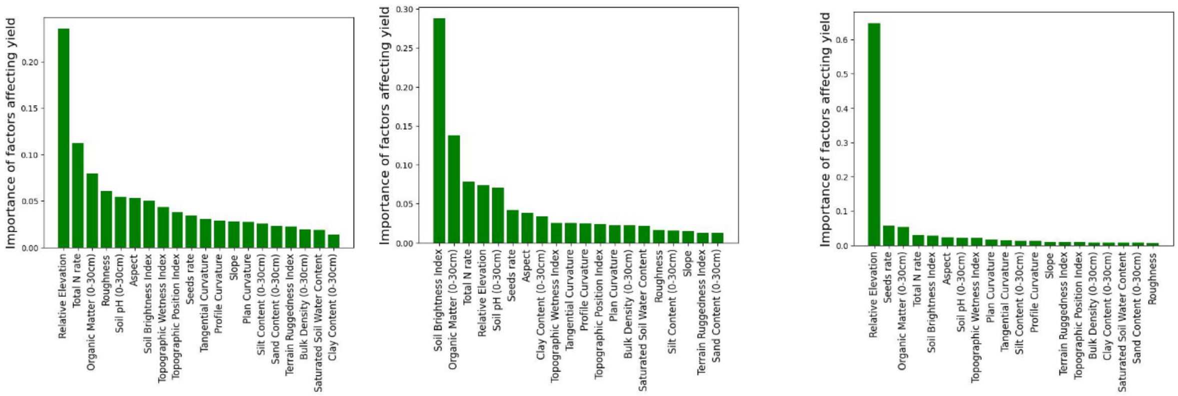


Figure 12. Key factors influencing corn yield identified using machine learning models in F15(left), F18(middle) and F19 (right).

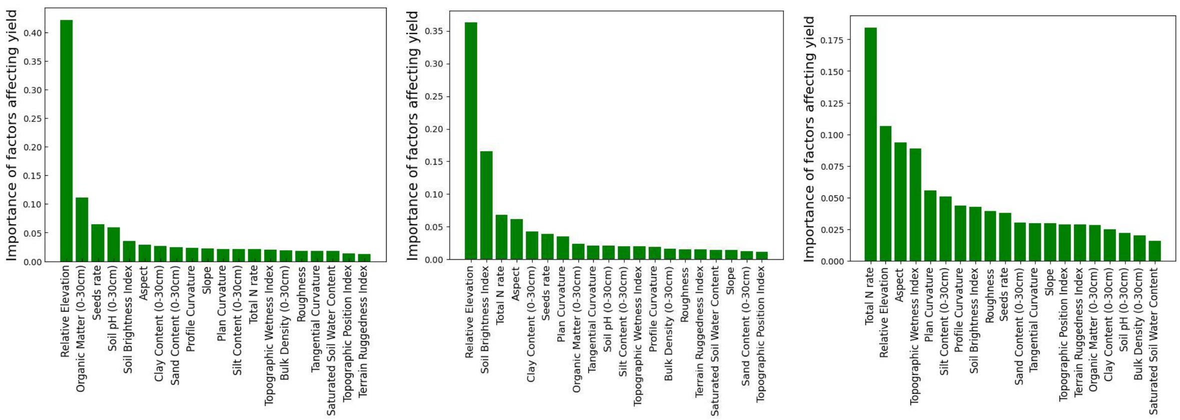


Figure 13. Key factors influencing corn yield identified using machine learning models in F21(left), F-Morris(middle) and F-Hack2 (right).

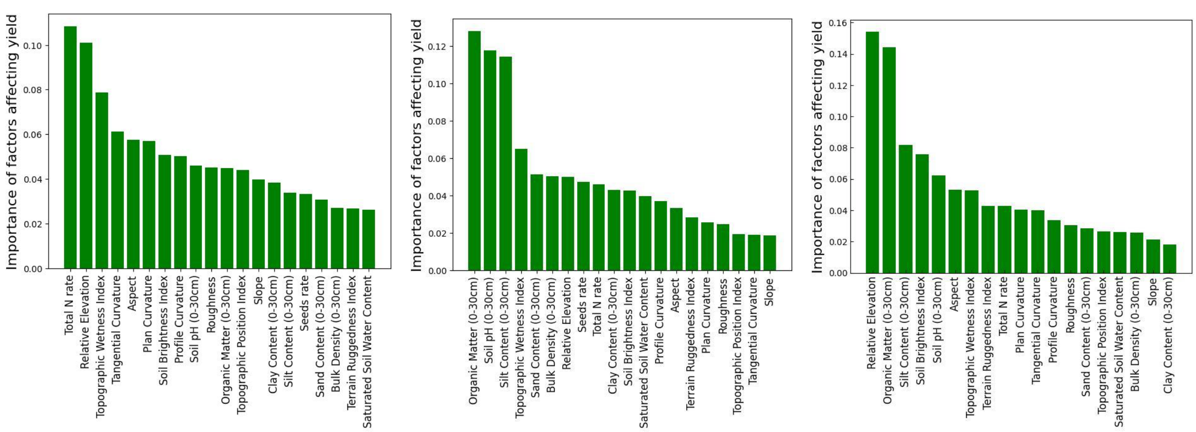


Figure 14. Key factors influencing corn yield identified using machine learning models in F-Gusw2(left), F-Brown(middle) and F-NeilW (right).

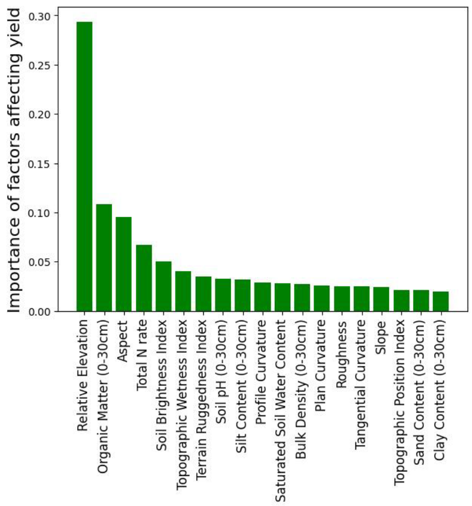


Figure 15. Key factors influencing corn yield identified using machine learning models in F-Lohmans.

Objective 3. Management zone delineation strategies in different regions.
This part of the results will need to wait for more results from Objective 2.

Objective 4. Support on-farm trials to evaluate different variable rate N strategies and technologies.

13 on-farm N trials were conducted in Minnesota in 2023, involving 3 irrigated fields, 3 fields with manure application, and 7 normal commercial fields. The on-farm trials were successfully implemented, and in-season sidedress N prescriptions were created by our group and applied by the farmers. In general, the applications were quite accurate. Soil and plant samples were collected around V8-V10.

We have analyzed all the 13 on-farm N trials conducted in Minnesota in 2023, involving 3 irrigated fields, 3 fields with manure application, and 7 normal commercial fields. A report was written, and we scheduled a meeting with each farmer to go over the results and discuss implications for their N management.

Objective 5. Facilitate the adoption of variable rate N technologies by developing variable rate N guidelines in Minnesota.

1) On-line decision support tool development:
We have developed an automation algorithm in Python to design strip trials, produce preplant N prescription (Figure 16), SideDress-Prescription Workflow uses PlanetScope high-resolution imagery to generate NDVI maps and create NDVI response curves. This helps specify Block-specific N Rate based on Pre-Plant Nitrogen (Figure 17). We are currently designing a web page about the PNM Tool (Figure 18). In the next step, we will further automate the in-season N recommendation process and incorporate the automation algorithm into the online system.

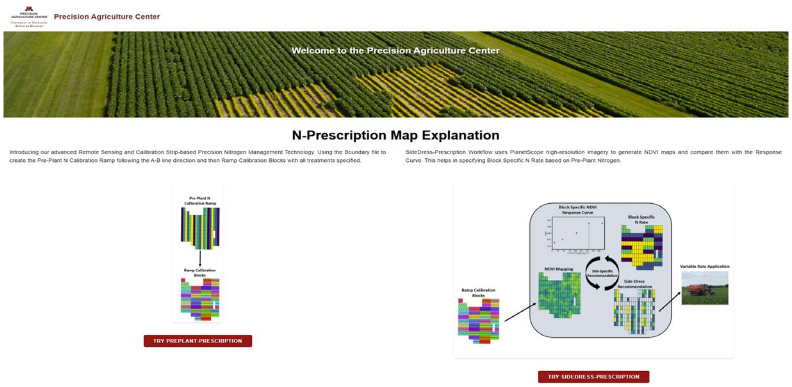


Figure 16. The open-source PNM Tool homepage being developed by University of Minnesota.

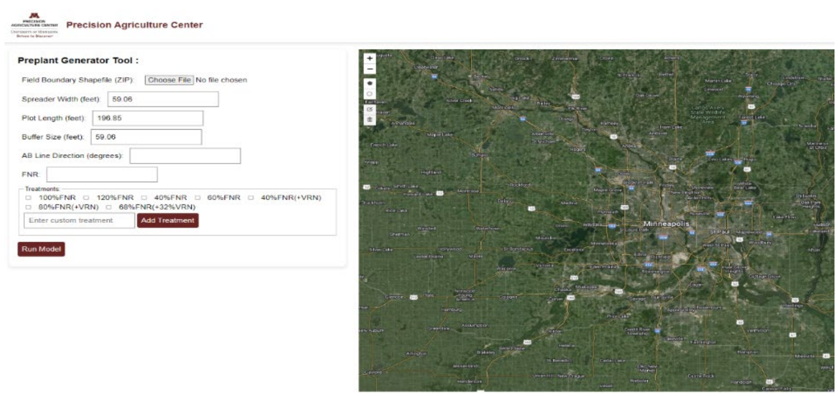


Figure 17. The preplant generator Tool being developed by University of Minnesota.

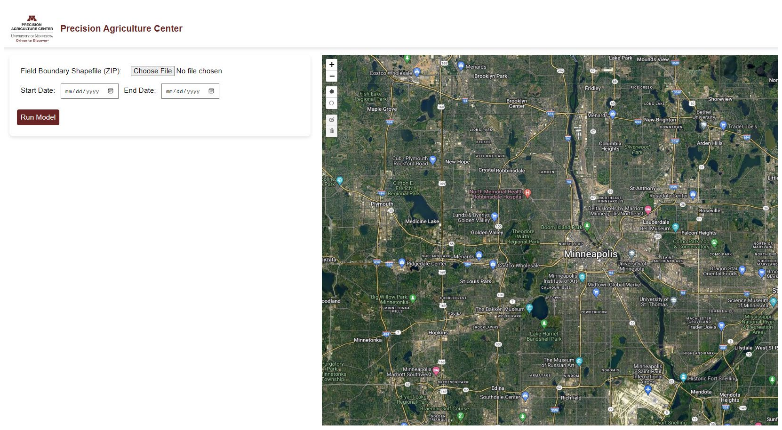


Figure 18. The sidedress generator Tool being developed by University of Minnesota.

2). On-farm Precision Agriculture Trial Network:

We have been organizing annual On-farm Precision Agriculture Trial Network summary meetings as a platform to connect farmers, consultants, researchers, postdocs, graduate students, partners from the industry, extension people, and partners from the state Department of Agriculture to meet and share on-farm trial results, experiences, challenges and suggestions for future improvements. On Feb. 15, 2024, we organized this year's network meeting in Minnesota to share 2023 on-farm trial results and discuss plans for 2024 (Figure 19). The participants included collaborative growers, crop consultants, university researchers, graduate students, an USDA ARS scientist, Minnesota Department of Agriculture scientists and industry collaborators. In addition to the in-person meeting, an on-line option was also provided to those who could not join in person. This is an annual event to facilitate interactions among researchers, extension educators, growers, crop consultants, industry service providers, and governmental researchers and policy makers. With this closer relationship, we can better understand the complexity of the issues producers face daily, share experiences and insights, and work together to develop innovative solutions, leading to a thriving and sustainable farming community.

Figure 19. 2024 MN On-farm Precision Agriculture Trial Network Meeting.

3). Field days, local, national and international conference presentations:

Yuxin Miao gave a presentation on precision N management on-farm trials at Soil and Water Conservation Society Annual Meeting held in Des Mones from August 6-9, 2023. He introduced the precision N management technology to farmers at a field day event organized in Becker on August 10. He also gave an update on the project progress at the AFREC summer meeting on August 17 (Figure 20).

Figure 20. Dr. Yuxin Miao introducing the precision N management technology to farmers at the field day event on August 10 in Becker, MN.

Two oral presentations were given by a graduate student and a postdoc at the ASA-CSSA-SSSA Annual Meeting on the progress of the project.

Lu, J. (Post Doc), Miao, Y., Mizuta, K., Negrini, R., Ona, A. G. M., & Quinn, D. (2023). Developing a Machine Learning-Based in-Season Site-Specific Nitrogen Recommendation Strategy for Corn Using Satellite Remote Sensing and Multi-Site-Year on-Farm Trial Data. ASA-CSSA-SSSA.

Negrini, R. (Graduate Student), Miao, Y., Mizuta, K., Lu, J., Lacerda, L. N., Ona, A. G. M., & Quinn, D. (2023). In-Season Prediction of Nitrogen Nutrition Index in Commercial Corn Fields with High Spatial and Temporal Resolution Planetscope Satellite Remote Sensing and Multisource Data Fusion. ASA-CSSA-SSSA.

Dr. Yuxin Miao gave an oral presentation on the Precision N Management project at the 2024 International Conference for On-Farm Precision Experimentation in Texas in Jan., 2024.

Yuxin Miao, Katsutoshi Mizuta, Junjun Lu, Ana Morales Ona, Renzo Negrini, Lorena Lacerda, Daniel J. Quinn, Jeffrey Coulter, David Mulla (2024) On-farm Evaluation of a Practical and Innovative Satellite Remote Sensing-based Precision Nitrogen Management Technology. International Conference for On-Farm Precision Experimentation, South Padre, TX. Jan. 7-11, 2024. (Oral)

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Dr. Katsutoshi Mizuta, a Postdoctoral in this program from University of Minnesota, gave the results at the 2024 International Conference for On-Farm Preision Experimentation in Texas and gave a presentation (oral) about the NRCS On-Farm Precision Nitrogen Management Project at the **academic/scientific events** listed below:

Katsutoshi Mizuta, Yuxin Miao, Junjun Lu, Renzo Negrini (2024) Evaluating Different Strategies to Analyze On-farm Trial Data: A Case Study for Nitrogen Trials. International Conference for On-Farm Precision Experimentation, South Padre, TX. Jan. 7-11, 2024. (Oral)