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Pesticide & Fertilizer Management Division

AFREC R2022-22

FINAL REPORTING

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

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Project objectives:

1) Identifying key factors influencing corn optimum N rates using deterministic cropping system models.
2) Identifying key factors influencing corn optimum N rates using machine learning models.
3) Management zone delineation strategies in different regions.
4) Support on-farm trials to evaluate different variable rate N strategies and technologies.
5) Facilitate the adoption of variable rate N technologies by developing variable rate N guidelines in Minnesota.

General Background

The University of Minnesota's Precision Ag Center has been trying to create improved and easy to use variable rate N (VRN) technologies using management zone (MZ) based dynamic crop models, remote sensing, and machine learning technologies. Previously completed on-farm trials and other ongoing trials being conducted in Minnesota's Central, Metro, Southeast, and South-Central areas provide the data to further improve some of the VRN technologies and develop guidelines for VRN management of corn in various regions of Minnesota.

On-farm Trials Data Compilation

Previous and current on-farm trials data have been organized and structured in a way that can be used for the development of farm scale modeling and machine learning algorithms. The number of years for which the data was organized varies depending on the duration the site was under an experimental trial. The organized major data types include the site soil characterization, historical weather data, genetic characteristics of corn cultivars planted, and agronomic management practices.

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

Model Calibration:

The CERES-Maize model was calibrated using the GM field, which was divided into 120 grids. To capture the variability in soil types within a field, some of the plots were subdivided into sub-grids. This has increased the total number of grids(plots) with the sub-grids (plots) to 164. The simulation time was set over three years, 2019-2021. The years 2019 and 2020 was used for model warmup, and the year 2021 was used for the detailed analysis of water budget, N budget and yield analysis.

The model simulated yield (calibration) and measured yield are shown in Table 1.

Table 1. Calibrated vs measured corn yield for calibration plots

Grid ID	Yield kg/ha	Calibrated Yield bu/ac	Measured yield, bu/ac	Soils	Applied N Fertilizer kg/ha
Grid 4	14922	220	226	400453	154
Grid 16	13574	200	198	400486	179
Grid 17	11449	169	167	400466	179
Grid 85	16366	242	241	400447	179
Grid 159	13261	196	200	400453	184

The calibrated CERES-maize module of the DSSAT-CSM was used to simulate nitrogen management responses to corn yield for five different treatments and 120 plots at Grand Meadow experimental field located in Southeast Minnesota. The calibrated model simulation efficiency was validated against measured yield using three different statistical measures: probability of bias (pbias), Nash-Sutcliff equation (NSE), RMSE-observations standard deviation ratio (RSR).

Nash-Sutcliffe efficiency (NSE): NSE is a normalized statistic that assesses how much residual variance ("noise") there is in relation to the variance of measured data (Nash and Sutcliffe, 1970). NSE represents how well the 1:1 line fits the observed versus simulated data plot. Equation 1 illustrates how NSE is calculated:

Equation 1

$$\mathrm{NSE} = 1 - \left[\frac{\sum_{i=1}^{n} (Y_i^{obs} - Y_i^{sim})^2}{\sum_{i=1}^{n} (Y_i^{obs} - Y^{mean})^2} \right]$$

Where: Y_i^{obs} is the ith measurement/observation, Y_i^{sim} is the ith simulated value, Y^{mean} is the mean of observed data, and n is the total number of observations.

Percent bias (PBIAS): PBIAS assesses the typical likelihood of the simulated data to differ from their observed counterparts in size or shape. Low-magnitude values of PBIAS indicate accurate model simulation, with 0.0 being the ideal value. PBIAS values that are positive suggest model underestimation bias, while values that are negative indicate model overestimation bias (Gupta et al., 1999). Equation 2 is used to determine the PBIAS:

Equation 2

$$\mathrm{PBIAS} = \left[\frac{\sum_{i=1}^{n} (Y_i^{obs} - Y_i^{sim}) * (100)}{\sum_{i=1}^{n} (Y_i^{obs})} \right]$$

RMSE-observations standard deviation ratio (RSR): RSR is calculated as the ratio of the RMSE and standard deviation of measured data, as shown in equation 3. RSR varies from the optimal value of 0, which indicates zero RMSE or residual variation and therefore perfect model simulation, to a large positive value. The lower RMSE, the lower the RSR, and the better the model simulation performance.

Equation 3

$$\mathrm{RSR} = \frac{\mathrm{RMSE}}{\mathrm{STDEV}_{obs}} = \frac{\left[\sqrt{\sum_{i=1}^{n} (Y_i^{obs} - Y_i^{sim})^2} \right]}{\left[\sqrt{\sum_{i=1}^{n} (Y_i^{obs} - Y^{mean})^2} \right]}$$

Simulated corn yield was validated against measured yield for a total of 32 plots under the four soil types (Figure 1). The average simulated corn yield for the 100% FNR treatment was 227 bu/ac, the measured average corn yield being 225 bu/ac. The statistical comparison in between the measured and simulated corn yield has shown NSE of 0.83, Pbias -0.60 and RSR 0.41. This indicates very accurate simulation results.

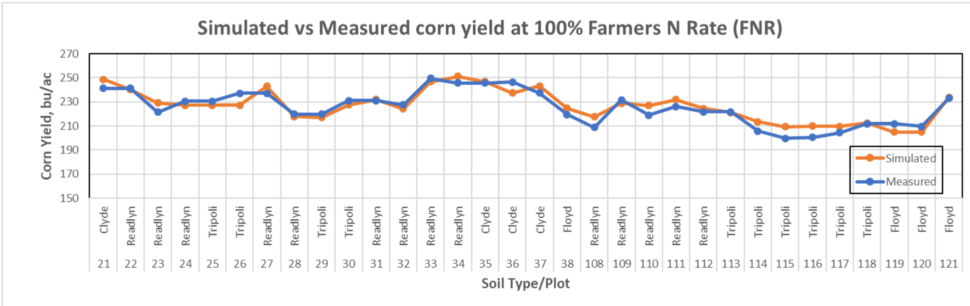

Figure 1. Simulated vs. measured corn yield of the farmer practice (100% farmer N rate).

Simulated Nitrogen Balance

A N balance, calculated as the difference between N inputs and N removal/outputs from the soil, provided an estimate of the potential N loss amounts. Soils and climate databases with detailed management practices were used as model inputs so as to identify drivers of N balance variation among the 120 plots of GM experimental site. The 35% FNR+CS treatment received the least N fertilizer, as seen in the table below, whereas the 130% FNR treatment received the most. The 130% FNR and 35% FNR + Granular have the largest nitrate drainage losses and leaching losses.

Table 2. Simulated N balances of different N management strategies.

N-Balance Components	N-INPUT, kg/ha				
	100% FNR	**130% FNR**	**35%FNR+CS**	**35%FNR+Granular**	**70%FNR+CS**
Fertilizer N	203.1	223.1	157.9	176.3	190.8
Mineralized N	69.6	64.7	66.0	65.6	62.6
Soil NH4	0.2	0.2	1.1	0.6	0.5
Soil NO3	58.5	53.5	65.7	81.0	70.3
Total N Input	331.4	341.5	290.8	323.5	324.4
N-Balance Components	**OUTPUT, kg/ha**				
	100% FNR	**130% FNR**	**35%FNR+CS**	**35%FNR+Granular**	**70%FNR+CS**
N immobilized	3.4	4.2	3.7	3.9	3.4
N leached	7.2	9.2	6.2	8.3	7.1
N loss to tile drainage	35.6	41.1	15.1	42.8	32.6
N Uptake from Soil	266.8	275.7	251.4	254.3	262.1
N2 loss	2.8	0.8	3.1	2.4	2.3
N2O loss	0.4	0.3	0.2	0.2	0.3
NH3 loss	2.2	0.6	1.5	1.1	1.0
NO loss	0.1	0.1	0.1	0.1	0.1
Soil NH4	0.2	0.2	0.2	0.2	0.2
Soil NO3	12.6	9.3	9.2	10.1	15.3
Total N Removal	331.4	341.5	290.8	323.5	324.4

Simulated Economic Optimum N Rates

The GM field was divided into 24 transects involving different N management strategies laying on four different soil types (Figure 2-4). The model simulation process involved the evaluation of corn yield response to varying N rates using different N management strategies in a tile drained high organic matter mollisol (Figure 2). The analysis focused on the influence of soil type on economic optimum N rate (EONR).

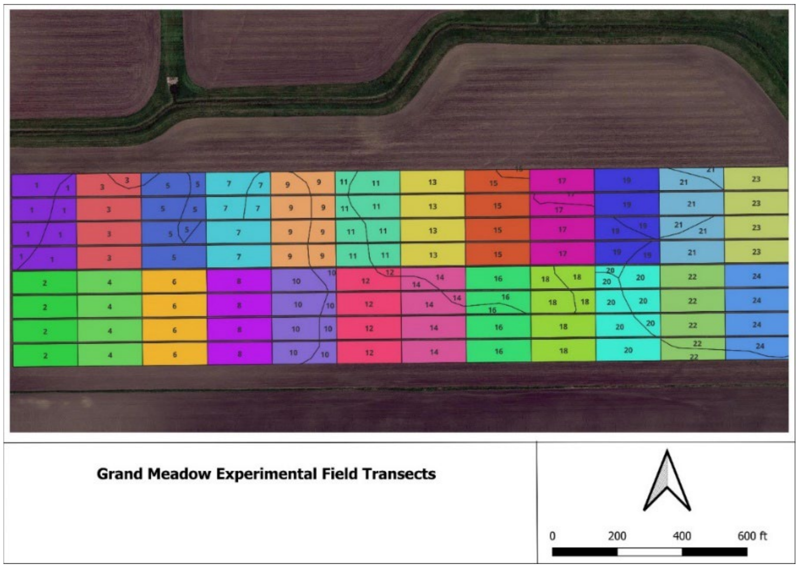

Figure 2. Transects delineated in the Grand Meadow study field.

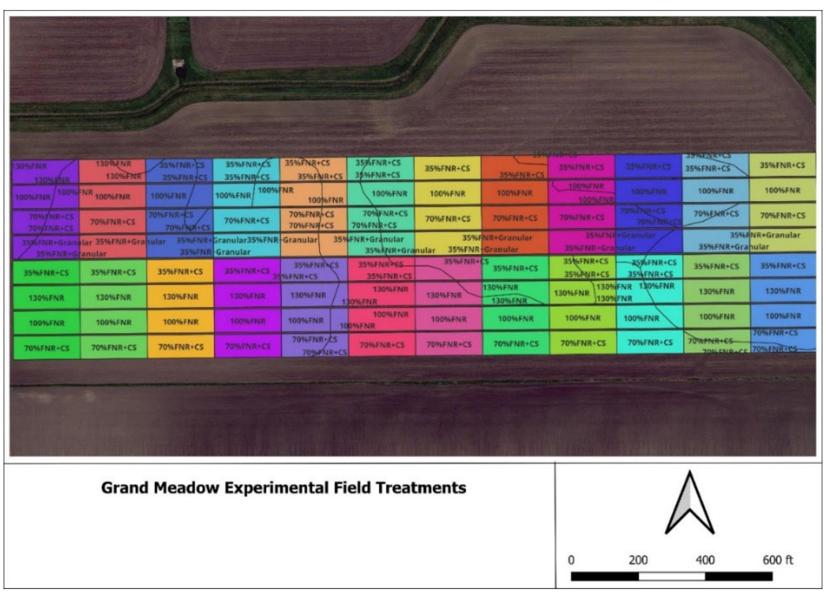

Figure 3. Different nitrogen management strategies involved in this field study in 2021. 130%FNR: 1320% of farmer's N rate all applied before planting. 100%FNR: 100%FNR all

applied before planting. 70%FNR+CS and 35%FNR+CS: 70%FNR and 35%FNR were applied before planting, and variable rate sidedress N application using calibration-strip based recommendation.   35%FNR+Granular: 35%FNR were applied before planting, and variable rate sidedress N application using service offered by Granular based on modeling.

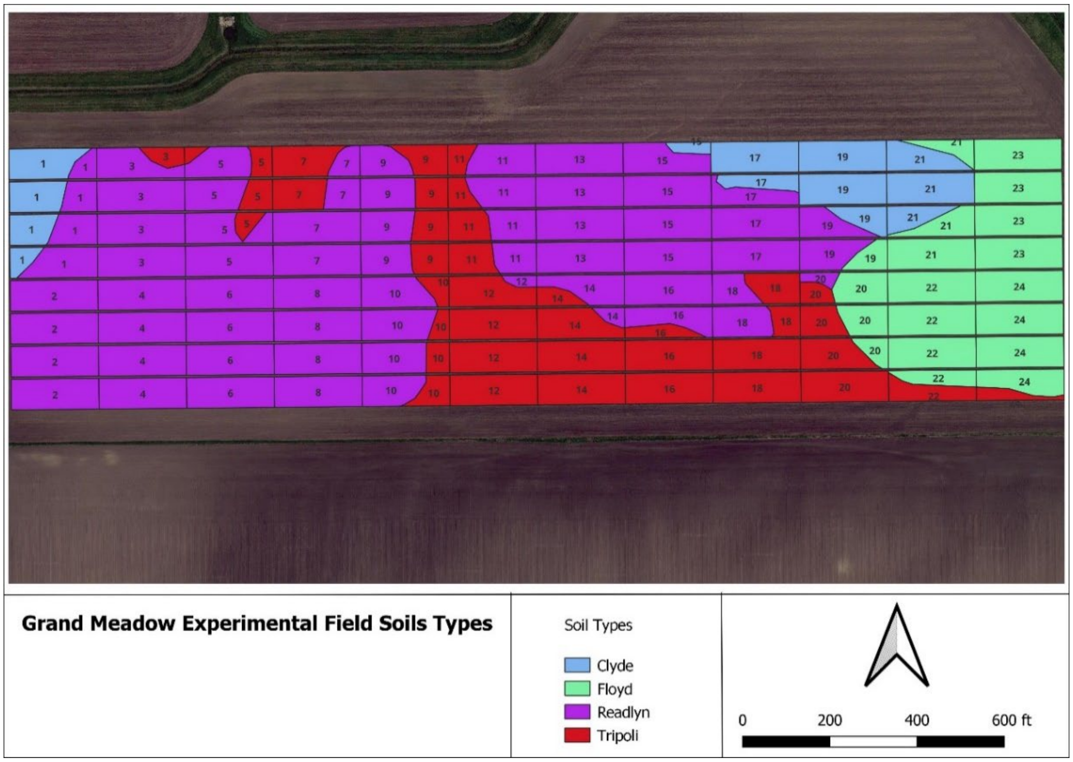

Figure 4. Four different soil types in this study field.

The N application rate at 100% FNR was 190 kg/ha or 170 lb/ac. This includes fall application of 24kg N/ha (21.4 lb N/ac) from monoammonium phosphate (MAP) and 6.5 kg/ha (5.8 lb/ac) from urea ammonium nitrate solution (UAN). To analyze the EONR, the corn yield response was simulated for pre-plant nitrogen application rates of Urea fertilizer at a rate of 0 kg/ha up to 260kg/ha (0-232 lb/ac) using 2021's weather data (Figure 5).

The results indicated that the EONRs ranged from 143 lb/ac to 161 lb/ac for different soil types and were lower than the farmer's N rate of 170 lb/ac. Soil type had a moderate influence on the EONR in this field in 2021, with a difference of 18 lb/ac among different soil types.

More analyses are being performed to determine the influence of sidedress timing and different weather conditions and the results will be reported in next report.

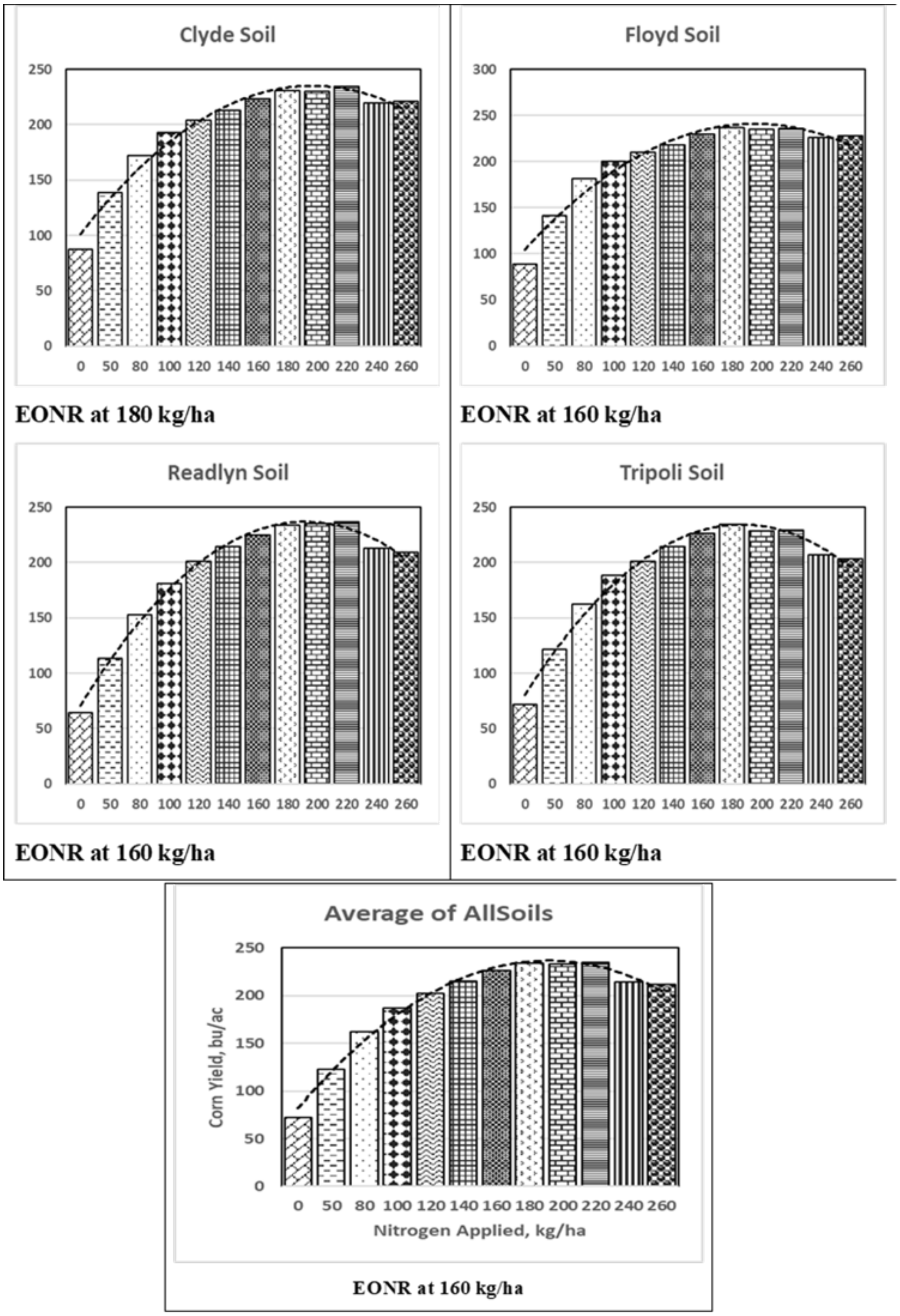

Figure 5. Simulated economic optimum nitrogen rate (EONR) for preplant application ranged from 160 kg/ha to 180 kg/ha (143-161 lb/ac) for different soil types, with the field average RONR being 160 kg/ha (143 lb/ac).

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

The objective of this study is to use machine learning models to identify key soil and landscape properties affecting yield spatial patterns and yield temporal stability for management zone delineation and to evaluate the consistence of these factors in different prediction models.

The study was carried out in a 44 ha corn-soybean rotation field in western Minnesota, USA. Yield maps from 7 years collected from 2014 to 2020 were used to create yield spatial trend (YST; average normalized yield map) and yield temporal stability maps (YTS; coefficient of variation map). In the complete dataset, 29 different soil and landscape properties were used as input in the machine learning models including relative elevation, slope, curvature and aspect, calculated from LiDAR elevation data at 1 m resolution downloaded from the MN TOPO website; topographic wetness index and soil brightness index calculated from PlanetScope images at 3 m spatial resolution; soil physical properties, and macro and micronutrients collected with SoilOptix, a high-resolution soil mapping system; and shallow and deep electrical conductivity. A farmer-friendly dataset was also tested using mostly variables that are available online and that can be easily accessed by farmers. All maps were interpolated to a 3 m grid using kriging.

Prediction models for YST and YTS were created using random forest, support vector machine and XGBoost algorithms. To identify features that were relevant for the models, Boruta algorithm was used for feature selection. Once features were selected based on importance, Spearman correlation was used to exclude features that were highly correlated to each other to avoid redundance. Results showed that while all features were deemed important, relative elevation was the most relevant factor influencing both YST and YTS. In the farmer-friendly dataset, soil brightness index was the most important feature for YST, and relative elevation was the most important for YTS (Table 3, Figure 7 and 8). Other attributes such as slope, iron, sulfur, potassium and calcium soil concentrations and soil organic matter were also among the most important factors for both YST and YTS. Random forest was the best performing model among all models and test dataset for both response variables.

Fig. 6. Location and boundary of rainfed corn-soybean rotation field used for the study. The field has an area of 44 ha and is located in the Traverse County, MN, USA.

Table 3. Complete list of variables used in the yield temporal trend (YTS) and yield spatial trend (YST) prediction models. Bold variables represent the variables included in the farmer-friendly dataset.

Labels	Variables	Labels	Variables
BI	**Brightness Index**	**Ec Shallow**	**Electrical Conductivity (shallow layer)**
CEC	Cation Exchange Capacity	**Ec deep**	**Electrical Conductivity (deep layer)**
-	**Relative Elevation**	-	Loam
-	**Slope**	-	Sand
K	Potassium	Plant avail. water	Plant Available Water
S	Sulfur	-	Leakability
-	**Aspect**	**TWI**	**Topographic Wetness Index**
Fe	Iron	B	Boron
Ca	Calcium	Mn	Manganese
P	Phosphorus	Mg	Magnesium
Cu	Copper	Ca-Mg ratio	Calcium- Magnesium ratio
OM	**Organic Matter**	K-Mg ratio	Potassium- Magnesium ratio
Zn	Zinc	pH	pH
-	Clay	Silt	Silt
-	**Curvature**		

The identification of key attributes that affect yield spatial and temporal variability in a field can greatly contribute to the delineation of representative management zones for site-specific application. Results showed that different soil and landscape attributes had varying roles in predicting crop yield, and that field data easily available could be used to predict crop yield and delineate management zones. Despite the promising results more research is required to test the relevance of different attributes across multiple fields and conditions. The next steps for this research will be to delineate management zones based on the prediction model results and analyze the yield variability within each zone. In the future, this pipeline for management zone delineation will be tested for nitrogen management, and potential economic and agronomic benefits will be analyzed.

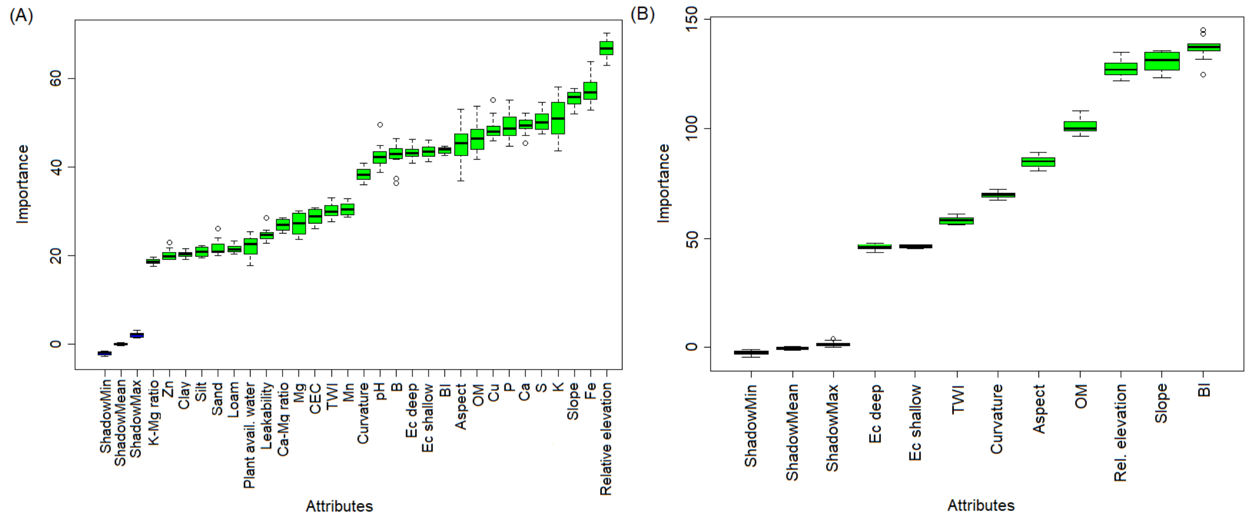

Figure 7. Boruta algorithm feature selection results for yield spatial trend (YST) prediction using the complete dataset (A), and the farmer-friendly dataset (B).

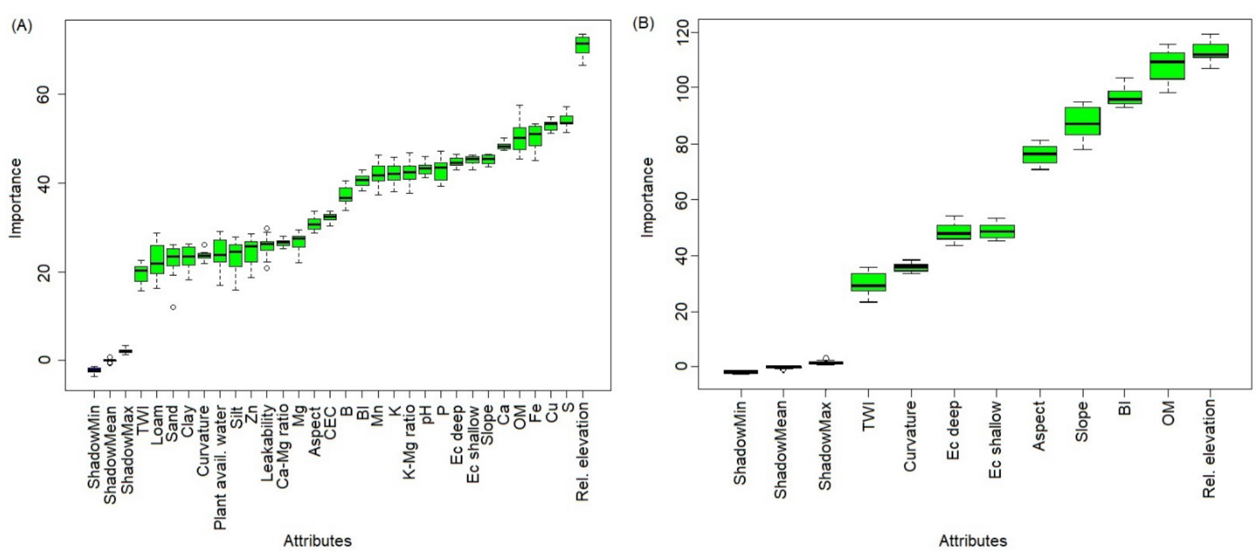

Figure 8. Boruta algorithm feature selection results for yield temporal stability (YTS) prediction using the complete dataset (A), and the farmer-friendly dataset (B).

In 2022, nine on-farm N trials were conducted in Minnesota, and all the data have been compiled, and preliminary analyses have been done for each field. The key results are summarized here.

1) In Minnesota, 2022 had a dry summer in most trials, and as a result, split-applications did not perform as all preplant application strategies under dry summer conditions. However, in general, the UMN precision N management strategy performed better than fixed rate split strategies farmers use.
2) Compared with farmer's N rate (FNR) and/or farmer's N practice, the UMN PNM system on average used 12 lb/ac less N (from 32 lb/ac less to 3 lb/ac more N on a field average

basis), achieved similar yield (yield difference varied from -13.2 to 18.3 bu/ac, with the average being 0.64 bu/ac on a field average basis). The N use efficiency (partial factor productivity, bu/lb N) increased an averaged 0.06 bu/lb N across all the trials, varying from an increase of 0.24 to a decrease of 0.19 bu/ac on a field average basis, depending on the field and farmer's management practices.

3) In general, we found that the UMN CS-RS-PNM technology determining site-specific sidedress N based on crop growth during the growing season resulted in higher yield and profits than the farmer's normal fixed rate split application practices based on the farmer's experience or suggestions from experts. However, the best performing N management strategy varied within a field or across fields due to the prices of fertilizer, corn, and field conditions (soil type, topography) and weather patterns.
4) Nitrification inhibitor: In a field study, we tested the effects of nitrification inhibitor of sidedress N application. The nitrification inhibitor worked quite well when 60%FNR was applied before and at planting and 40%FNR was sidedressed. The addition of nitrification inhibitor resulted in 9 bu/ac higher yield and 51 $/ac higher profit than the same treatment without nitrification inhibitor. However, when 40%FNR was applied before or at planting with variable rate sidedress N application, the addition of nitrification inhibitor did not produce any benefits in profit.
5) In general, in dry years or dry regions, the 100%FNR or 80%FNR +VRN sidedress can perform better than 40%FNR+VRN sidedress or 60%FNR+VRN sidedress, while in wet years or wet regions, 40%FNR+VRN sidedress or 60%FNR+VRN sidedress generally perform better than 100%FNR or 80%FNR +VRN sidedress.
6) In an irrigation field located in Becker, the 30%FNR +VRN sidedress strategy performed the best, with the highest agronomic, economic and environmental benefits.
7) No single N management technology performed the best across fields or across a field. Different strategies performed better in different parts of a field depending on the soil type, OM content, landscape positions and weather conditions (Figure 9 and Table 4 for example).
8) The UMN PNM system incorporates different N management strategies involving both all-preplant N application and split applications with variable rate sidedress N and has built in a mechanism of insurance, therefore, it is more stable and adaptive to different weather conditions than only using one strategy or technology.

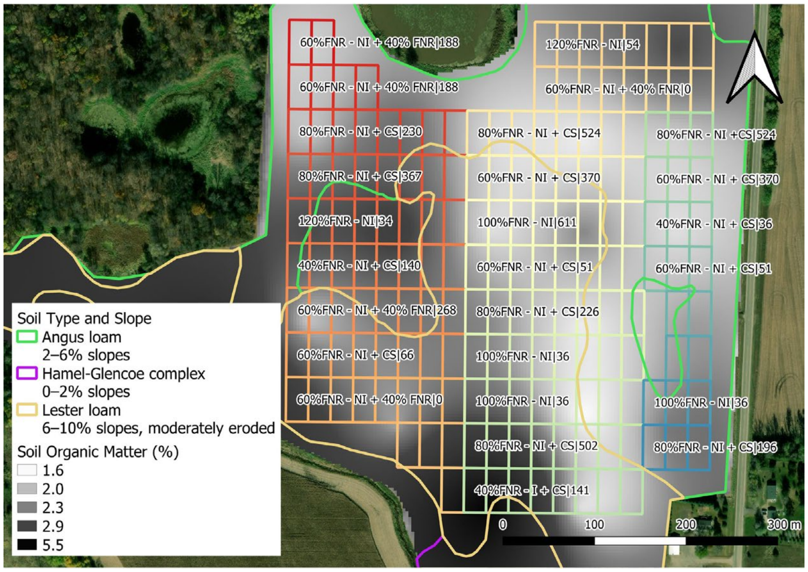

Figure 9. Map of an optimal technology and additional profits ($) for each or transect. Soil type and slope data were from Web Soil Survey. Soil organic matter content (%) estimated using a geospatial model based on 2019 lab-measured data. The best economically optimal technology was written on the left of the label within a block, while the number on the right side of label shows additional benefit ($) per grid produced by the optimal technology compared to farmer's normal practice (i.e., 60%FNR+40%FNR Urea-NI).

Note that the symbol + indicates the sidedress was applied after the preplant N application unless inhibitor application (I) followed immediately after the symbol. Also, the preplant and sidedress fertilizers were applied as prescribed with the accuracy of 98.9% and all the grids were considered for this map without removing any outlier grids for demonstration purpose, [Acronyms] CS: calibration-strip based sidedress prescription; FNR: farmer's N rate; I: with nitrification inhibitor; NI: no nitrification inhibitor.

Table 4. Areas within the entire field where each treatment/technology performed the best economically.

Optimal Treatment	**Areas Within Field** (%)
100%FNR + NI	21
120%FNR + NI	0
40%FNR + CS - I	5
40%FNR + CS - NI	7
60%FNR + 40% FNR - I	9
60%FNR + 40% FNR - NI	11
60%FNR + CS - NI	16
80%FNR + CS - NI	30
Total	100

More analyses will be performed based on the data collected from 2019-2022 to establish machine learning models to identify key variables influencing optimal N rates and will be reported in next report.

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.

Nine on-farm trials were conducted in 2022 to evaluate variable rate N management strategies. Plant and soil samples were collected at harvest time and yield data have been obtained from farmers. We analyzed all the data and prepared a report for each field and farmer. We organized an 2022 On-farm Precision Agriculture Trial Summary Meeting on Jan. 20, 2023 to invite all the cooperative farmers and crop consultants to join this meeting by a combination of in-person and on-line format (Figure 6), and we shared the overall findings and implications of 2022 trials. We also organized one-to-one meetings to discuss the results with each farmer/consultant to help them understand the results and discuss 2023 plans.


Figure. 4. Minnesota Annual On-farm Precision Agriculture Summary Meeting (January 20, 2023)

Objective 5. Facilitate the adoption of variable rate N technologies by developing variable rate N guidelines in Minnesota.
Need to wait until more results are available from previous objectives.