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# Minnesota Department of Agriculture
# Pesticide & Fertilizer Management
## FINAL REPORT
## FOR THE PERIOD: JANUARY 1, 2014 – MARCH 31, 2020

PROJECT NUMBER: 63924

PROJECT DESCRIPTION: **Comparison of real-time N stress sensors and remote sensing from unmanned aerial vehicles for precision management of N fertilizer and improvement of water quality**

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## Executive Summary

Nitrogen management practices which focus on applying the right rate at the right time have been proposed to reduce N loads to surface waters for a number of years. Sidedress variable rate nitrogen fertilizer (VRN) application addresses both the temporal and spatial asynchrony that occurs with single uniform pre-plant applications. Though sidedress VRN fertilizer application has the potential to reduce nitrate-N loads to surface waters from agricultural fields, there has been little research on how it compares to conventional single, uniform application in this regard. Three direct study objectives arise out of this background information. The first objective is to: 1) Compare the performance of UAV-based multispectral remote sensing to well-established handheld chlorophyll meter and CropCircle sensing for quantifying N status in corn at different growth stages and locations in Minnesota. The second objective is to: 2) Evaluate the effectiveness of N sidedressing on corn yield based on multispectral remote sensing. The third objective is to: 3) Assess the benefits of variable rate sidedress N fertilizer application on losses of nitrate-N in subsurface tile drainage systems.

In a first set of experiments, corn was grown in four fields in southern Minnesota (Janesville, New Richland, Theilman, and St. Charles) from 2013 to 2014 using a randomized complete block design. An octocopter equipped with a Tetracam Mini-Multiple Camera Array system was used to capture aerial imagery at three corn growth stages (V6, V10, R2). Vegetation indices computed from UAV/multispectral imagery were compared to SPAD chlorophyll readings and ground-based CropCircle optical measurements. UAV–derived indices coupled with estimates of economically optimum nitrogen rates (EONRs) were used to quantify in-season corn nitrogen stress and to compare sidedress efficacy of regional based nitrogen recommendations. Higher

EONRs were observed at coarser-textured soil locations with lower soil organic matter. Green difference vegetation index (GDVI) values were an accurate predictor of final yield at each growth stage and experimental site, especially for growth stages V10 and R2. UAV-derived block-normalized green ratio vegetation index (GRVI) and green normalized difference vegetation index (GNDVI) were strongly correlated with SPAD and CropCircle indices in estimating corn nitrogen status. Nitrogen sidedressing based on V10 differential EONR (dEONR) had efficacies of 87%, 80% and 71% for SPAD, UAV/GRVI and UAV/GNDVI respectively compared to pre-plant EONR application. Sidedress based on multispectral GRVI reduced nitrogen fertilizer use by 21% compared to the EONR without impacting yield.

In a second set of experiments, a 16-hectare field in southern Minnesota (Waseca) divided into nine independent subfields was planted to maize in the 2016 and 2017 growing seasons. Four subfields received variable rate N based on V6 sensing. VRN consisted of one third of the EONR applied before planting and the remaining sidedressed at V7. Four subfields served as controls and received conventional pre-plant application of N based on the EONR. Repeated measures ANOVA using three previous years of normalized yield data for four VRN subfields showed no impact of VRN on yield, despite significant reductions in fertilizer rate (33% , 24% and 52% compared to the EONR in 2016, 2017 and 2019, respectively). VRN subfields displayed significantly and consistently higher NUE values for both growing seasons, with an average NUE of 96%. Lastly, VRN for maize based on in-season sensing paid off every year, even in the absence of yield increases, because of the N savings that resulted from utilization of soil N.

Using data from the second set of field experiments described above, the field-scale hydrologic and nitrogen simulation model Drainmod-NII was used to predict nitrate loads over a 14 year period (2003-2019) for different fertilizer application rates and timing to corn at Waseca in southern Minnesota, USA. The fertilizer practices simulated included a single application in the spring before planting, a split application with half applied pre-plant and half at approximately the V6 stage for corn, and split and variable rate N practice (VRN) which utilized the split timing and a lower rate based on in-season monitoring of plant N requirements. Field trials in 2016, 2017 and 2019 of VRN application at the Waseca AERF site were used to inform the nitrogen rates used for the VRN scenario simulated, and to validate model performance in simulating daily nitrate concentration for subfields receiving VRN application. Comparison of Drainmod model results for nitrate concentration data measured for the 2016, 2017 and 2019 growing seasons showed good agreement between measured and predicted nitrate concentrations. Alternative nitrogen fertilizer application strategies that change the timing or rate and timing of fertilizer to more closely match plant nitrogen requirements reduced nitrate-N loads from corn and soybean cropping. For a 14 year simulation, model results for split sidedress N applications showed a 28% average annual reduction in N load compared to a single pre-plant application, while VRN sidedress N application showed a 41% reduction. The larger decrease in the average annual nitrate load for the VRN application, which utilized a reduced fertilizer rate in addition to split fertilizer application timing, indicates that while changing the timing of fertilizer application reduces N load, changing the rate has an important impact as well. Model simulations showed that changes in nitrogen application timing also reduced the amount of mineralized SOM, and reduced residual soil nitrogen.

To regionalize the modeling results observed at the Waseca study described above, Drainmod-NII was used to estimate nitrate-N loads for fertilizer applied to corn given different application rates and application timing approaches for three sites in southern Minnesota: Waseca, Willmar, and Lamberton. The results of these simulations were used in a regression analysis to develop equations to predict nitrate-N losses for southern Minnesota as a function of fertilizer timing and application rate, as well as growing season precipitation. Fertilizer timing treatments used in model simulation included fall, spring, and variable rate nitrogen (VRN) applications. The VRN application involved half of the total fertilizer rate applied in the spring before planting, with the remaining half applied at approximately corn V6 growth stage. The results of the Drainmod simulations showed the highest nitrate loads occurred for all fall application rates, with VRN having the lowest predicted N losses. An exponential regression model which used fertilizer application rate and growing season precipitation as the dependent variables had good agreement with Drainmod results, with $R^2$ values of 0.56, 0.53, and 0.53 for spring, split-VRN, and fall application, respectively. The regression model showed that the variation in the Drainmod predicted nitrate-N load for the different application timing treatments was highly related to annual precipitation and fertilizer application rates. Results of regression modeling showed that at 80 cm of precipitation and an application rate of 120 kg N $ha^{-1}$, N loads were reduced by 18% and 39%, respectively, for spring and split application compared to fall. Combining the split timing with lower rates—which could be achieved using VRN technologies—resulted in greater reductions in N losses. If producers switched from the current average timing and rate to split-VRN technology, annual regional reductions of 33% in nitrate-N losses would occur given a 10% reduction in N rate, or a 41% reduction for a 30% reduction in N rate. These results show that implementation of VRN sidedress applications based on remote sensing of crop N status can result in significant improvements in water quality.

## Acknowledgement

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CLEAN WATER LAND & LEGACY AMENDMENT

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## Project Rationale and Objectives

Nitrate-nitrogen (N) from fertilizer applied to subsurface tile drained corn cropping systems in the Upper Mississippi river basin is a cause of impairment to both fresh and marine water systems (David et al., 2010; Schulte et al., 2006). Its role in the development of one of the largest hypoxic zones in the world in the Gulf of Mexico has drawn intense scrutiny of N losses from agricultural lands in the Upper Midwest, with an estimate that nitrate-N entering the Mississippi River from upstream farm fields needs to decrease by at least 45% in order to reduce its size to a more reasonable extent (Committee on Environment and Natural Resources, 2010, US EPA, 2007).

In the Upper Mississippi river basin, nitrate-N loading from farm fields to surface waters is a function of subsurface drainage and soil nitrate concentration. Subsurface drainage rates peak in the months of April through June when soils thaw and plant evapotranspiration rates are low (Randall, 2004). Conventional fertilizer application occurs in the spring or fall before planting, greatly increasing the amount of nitrate-N present in the soil when drainage rates are high, and increasing the potential for nitrate loss. In a 15 year study in Minnesota, this 3-month period accounted for 71% of the annual drainage volume and 73% of the annual nitrate loss from a corn-soybean rotation (Randall, 2004). In addition to timing mismatches, farm fields in the upper Midwest can display significant within-field variability in soil organic matter and nitrogen content (Mamo et al., 2003; Scharf et al., 2005), yet more than two-thirds receive a blanket N application (Erickson and Widmar, 2015). This practice of uniform fertilizer application over fields with non-uniform soil-sourced nitrogen can result in higher losses of N (Power et al., 2000).

### Variable Rate Nitrogen Fertilizer Management

Nitrogen management practices which focus on applying the right rate at the right time have been proposed to reduce N loads to surface waters for a number of years (i.e. Nelson, 1985). Split-variable rate nitrogen fertilizer (VRN) application addresses both the temporal and spatial mismatches that occur with single uniform pre-plant applications. In this management, part of the total N amount is applied at or before planting, and part as side-dress during the growing season, delaying full application of fertilizer until corn growth stage V6-V8. Side dressing rates are based on spatial variations in plant N requirements, which can be variable based on crop sensing (Mulla, 2013) or in-season modeling of plant available N, reducing over-application of fertilizer on areas with high soil nitrogen content.

### Determination of Variable Sidedress N Fertilizer Rate

The challenge then becomes how to most appropriately compute N sidedress (SD) rates that account for within field spatial variability. The literature shows that N SD rates can be based on three main approaches. One option is to sidedress using a uniform rate based on the economic optimum nitrogen rate (EONR) or the maximum return to nitrogen (MRTN) while accounting for any pre-plant (PP) N application. While this method is simple to implement for growers, it fails to account for within-field spatial and temporal variability of the EONR and yield potential (Scharf et al., 2005; Scharf et al., 2006; Mulla, 1993; Mamo et al., 2003; Khosla et al., 2002). A second option for determining N SD rate relies on in-season modeling of the N budget at the field scale, and accounts for PP N amendments as well as organic matter N mineralization and the subsequent inorganic N release and loss. While this technique has the advantage of incorporating both pre-sidedress and short-term forecast weather conditions, therefore adjusting yield potential and N requirement when computing the N SD rate, it fails to account for the within field spatial variability and is typically subscription-based and is an added expense for growers (e.g., Adapt N and Climate Pro). A third option for computing SD is based on in-season remote and proximal sensing in conjunction with N rich strips (Schepers et al., 1992; Hatfield et al., 2008; Mulla 2013; Raun et al., 2002).

The main advantage of remote and proximal crop sensing over the previous two approaches is its ability to account for within-field spatial variability. Crop sensing also offers the ability to adjust N SD for yield potential using different homogeneous zones in the field (Roberts et al., 2012). Satellites are considered the dominant platform for in-season imagery in the Midwest because of their low cost. However, one of the shortfalls of satellite imagery is its susceptibility cloud cover and low temporal resolution (orbital return frequency). Satellite revisit time is critical as growers usually have a short time window for sidedressing due to plant height and soil wetness constraints. Therefore growers depend on a reliable and timely sidedressing imagery decision support system so as to avoid yield loss due to late timing of sidedress N application. Ground-based optical sensors (e.g., Greenseeker, Rapidscan and Crop Circle) have also been successfully deployed for in-season N management (Raun et al., 2002). However, except for sense and spread technology that permits real time N sidedressing (Scharf et al., 2011), the use of these devices is laborious. They often require driving and scanning the entire field, and may include significant sampling error when not every single plant is sensed.

With the recent advent in UAV technology, and multi-spectral sensors coupled with government relaxation of regulations governing commercial use of UAVs, growers now have a new tool that has the potential to revolutionize farming by providing timely and cost effective imagery-derived vegetation indices (VIs) that can be used for N sidedressing. Imagery captured by UAVs offer higher spatial resolution, which allows for the removal of soil background and mixed pixels from pure vegetation pixels. Imagery with higher spatial resolution also allows for computer vision techniques to be applied to quantify the level of N stress in plants (Zermas et al., 2015). UAV-based remote sensing application in N sidedressing is still in its infancy and research is needed to confirm its performance in the detection and quantification of N stress in corn so this technology can be deployed by growers and practitioners to improve in-season N management and NUE. The premise is that this technology is cloud cover resistant, and allows for flexible scheduling if farmers can overcome imagery processing, scalability and VI derivation. In this study, we propose to compare UAV derived VIs to well established proximal and remote crop sensing indices for in-season detection of corn N status.

Two direct study objectives arise out of this background information. The first objective is to: 1) Compare the performance of UAV-based multispectral remote sensing to well-established handheld chlorophyll meter and Crop Circle sensing for quantifying N status in corn at different growth stages and locations in Minnesota.  The second objective is to: 2) Evaluate the effectiveness of N sidedressing on corn yield based on multispectral remote sensing.

## Impacts of Variable Rate N Fertilizer Management on N Losses in Subsurface Drainage

In the heavily row-cropped, 4-million hectare Minnesota River Basin, approximately 60% of the soils are classified as poorly drained (Sands et al., 2006).  Subsurface tile drainage systems are beneficial to crops in agricultural soils characteristic of the Minnesota River Basin that have low water infiltration rates along with flat or depressional topography.  Subsurface drainage systems are connected to surface waters via a network of drainage ditches, which carry water and associated soluble pollutants from upland farm fields into streams, rivers, and lakes.  Nitrate losses through subsurface drainage systems are primarily determined by the volume of water transported through the drainage system, and the nitrate-N concentration in the soil.  Factors that influence these include: precipitation, crop maturity and evapotranspiration (ET) rates, soil organic matter content, and fertilizer management practices.

Drainage and nitrate load show a seasonal response, with higher flow and associated N loss occurring months  when there is little plant uptake of water or nitrogen.  For warmer regions where fields are fallow but not frozen during the winter, the peak flow and associated N loss occurs during this fallow winter period.  In Indiana, Kladivko et al., (2004) found that 81% of annual tile drainflow and 78% of N load occurs in the months November through April.  For northern areas of the Upper Mississippi River basin where soils remain frozen during the winter months, low ET rates and higher drainage volumes generally coincide with the spring months of April, May, and June.  In a 15 year study in southern Minnesota, these three months accounted for 71% of the annual drainage volume and 73% of the annual nitrate loss from a corn-soybean rotation (Randall, 2004).

Typical fertilizer application in southern Minnesota often occurs well before the largest N demands of the crop occur; nearly all fertilizer application occurs in fall before planting (MPCA 2013).  Fall application of N fertilizer has been show to result in the highest losses of N compared to other application timings.  Randall and Mulla (2001) showed that over a 6-year period for a continuous corn system at Waseca, MN, fall application of N fertilizer resulted in an average nitrate load that was 36% higher than a spring application.  Split application of nitrogen fertilizer addresses the asynchrony in timing between nitrogen application and plant uptake by applying part of the total N amount at or before planting, and part as side-dress during the growing season.  This approach delays full application of fertilizer until corn nitrogen uptake rates peak around growth stage V6-V8.

Though sidedress VRN fertilizer application has the potential to reduce nitrate-N loads to surface waters from agricultural fields, there has been little research on how it compares to conventional single, uniform application in this regard.  Gast et al., (1978) showed that a 50% decrease in fall fertilizer application rate from 224 kg N/ha to 112 kg N/ha resulted in an almost 58% reduction in nitrate load.  In a modelling study by Nangia et al. (2008), switching from fall to spring application resulted in a 9% decrease in nitrate losses.  Bakhsh et al. (2002), found a 25% reduction in N loss for a split application of N to corn compared to single spring application in

Iowa. In a modeling study using Adapt-N which compared nitrate losses for a split application versus a split application with a reduced rate, Sela et al. (2016) found that a 34% decrease in sidedress N application resulted in a 36% decrease in N losses.

A third objective for this study arises out of the need to achieve better water quality. This objective is to: 3) Assess the benefits of variable rate sidedress N fertilizer application on losses of nitrate-N in subsurface tile drainage systems.

Three related studies were established to achieve the three objectives of this project, corresponding to the following four chapters of the Final Report. The first study was to evaluate UAV based remote sensing of N deficiency for sidedress N fertilizer management and crop yield (Objectives 1 and 2) at four commercial maize farms (Janesville, New Richland, St. Charles and Theilman) in southern Minnesota during the 2014-2015 growing seasons (Chapter 1). The second study was to evaluate remote sensing for variable sidedress N fertilizer management, crop yield and water quality (Objectives 1, 2 and 3) at the Agroecosystem Ecology Farm (AERF) located on the Southern Research and Outreach Station in Waseca (Chapter 2). A third study (Objective 3) was to calibrate and validate the DRAINMOD NII model at the Waseca AERF site, as well as at Willmar and Lamberton field sites, in order to develop regional predictions of nitrate-N loss in subsurface drainage systems across southern Minnesota (Chapters 3 and 4).

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# Chapter 1: Unmanned Aerial Vehicles (UAVs) and Multispectral Sensing for Improved In-Season Nitrogen Management of Corn (*Zea Maize* L.)

## Introduction

Growers in the Midwest of USA are facing a dilemma of applying enough N fertilizer to sustain optimum corn yield while reducing the impact of N on the environment. This issue is unique to N because of a combination of logistic, edaphic, climatic, and agronomic factors (Lazarus et al., 2014). Agricultural fields in MN tend to be large, which predisposes these fields to significant within-field variability in soil organic matter and thus N mineralization and the subsequent plant available N (Malzer, 1996). Yet 80% of corn fields in the Midwest still receive uniform applications of fertilizer amendments.

To avoid wet spring and limited field-workable-day windows, many producers apply N fertilizer in the fall, a practice that is often incentivized by fertilizer dealers and custom applicators. For example, a recent MN survey found that one third of growers apply N fertilizer in the fall (Bierman et al., 2012), which increases the potential for N losses and contamination of both surface and ground water. The organic matter rich soils of southern MN further exacerbate the N issue. In southern and western MN the dominant soils are the deep and organic matter rich Mollisols and Alfisols that once supported prairie grassland (Cummins, and Grigal, 1981). While these soils are very productive with the organic matter supplying a significant, but variable, portion of the required crop N via mineralization, they do often require subsurface drainage to improve aeration and to increase the length of the growing season (Hill, 1976; Kanwar et al., 1988). In fact, the majority of agricultural fields in southern MN have been historically tile-drained (Wilson, 2000). However, an unintended consequence of artificial drainage is that tile drains are a direct conduit to surface water, so nitrate that escapes the root zone via leaching is directly transported to surface waters (MPCA, 2013).

The intensity and temporal distribution of precipitation make N management even more difficult. Aquic and udic soil moisture regimes dominate southern MN, and most rainfall is concentrated in the first two months of the growing season (May-June) when evapotranspiration rates are relatively low (Sands, 2015). This precipitation distribution results in significant agricultural runoff and leaching in this period (Sands et al., 2008). Since more than 90% of growers in MN apply their N fertilizer before planting (Bierman et al., 2012),, there is a high risk of moving this early applied N beyond the root zone in this period of the growing season (Sands et al., 2008). This is noteworthy because corn N uptake does not substantially increase until past the V6 growth stage (Abendroth et al., 2011), which tends to occur in mid- to late-June for a typical growing season in southern Minnesota (Angell et al., 2017). This combination of the aforementioned factors creates a time and space asynchrony between N amendment and crop demand, and is responsible for N loss via agricultural runoff, leaching, and volatilization. The use of slow release or delayed N fertilizer sources has the potential to delay ammonification and/or nitrification, and these products are offered to growers by most fertilizer dealers at an additional cost. However, research has shown that the return on investment (ROI) of these products is not consistent, and that the N protection offered by these products is short lived (Franzen, 2011; Malzer et al., 1989).

Alternatively, split N application has been recently gaining momentum as part of the best management practices for N. Growers can apply a small uniform amount of N at or before planting and delay the remaining N until near plant uptake peak at around growth stage V6-V8 (Abendroth et al., 2011). By matching the time of N amendment and that of peak crop uptake, nitrate movement offsite can be reduced, and growers' N investment can be protected.

Nitrogen sidedress (SD) rates can be based on three main approaches. One option is to sidedress using a uniform rate based on the economic optimum nitrogen rate (EONR) or the maximum return to nitrogen (MRTN) while accounting for any pre-plant (PP) N application. While this method is simple to implement for growers, it fails to account for within-field spatial and temporal variability of the EONR and yield potential (Scharf et al., 2005; Miao et al., 2006a; Scharf et al., 2006; Mulla, 1993; Mamo et al., 2003; Khosla et al., 2012). A second option for determining N SD rate relies on in-season modeling of the N budget at the field scale, and accounts for PP N amendments as well as organic matter N mineralization and the subsequent inorganic N release and loss. While this technique has the advantage of incorporating both pre-sidedress and short-term forecast weather conditions, therefore adjusting yield potential and N requirement when computing the N SD rate, it fails to account for the within field spatial variability and is typically subscription-based and is an added expense for growers (e.g., Adapt N and Climate Pro).

A third option for computing SD is based on in-season remote and proximal sensing in conjunction with N rich strips (Schepers et al., 1992; Hatfield et al., 2008; Mulla 2013; Raun et al., 2002; Hatfield and Prueger, 2010). The main advantage of remote and proximal crop sensing over the previous two approaches is its ability to account for within-field spatial variability. Crop sensing also offers the ability to adjust N SD for yield potential using different homogeneous zones in the field (Roberts et al., 2012). Satellites are considered the dominant platform for in-season imagery in the Midwest because of their low cost. However, one of the shortfalls of satellite imagery is its susceptibility cloud cover and low temporal resolution (orbital return frequency). Satellite revisit time is critical as growers usually have a short time window for sidedressing due to plant height and soil wetness constraints. Therefore growers require a reliable and timely sidedressing imagery decision support system so as to avoid yield loss due to late timing of sidedress N application.

Ground-based optical sensors (e.g., Greenseeker, Rapidscan and Crop Circle) have also been successfully deployed for in-season N management (Raun et al., 2002). However, except for sense and spread technology that permits real time N sidedressing, the use of these devices is laborious. They often require driving and scanning the entire field, and may include significant sampling error when not every single plant is sensed.

With the recent advent in UAV technology, and multi-spectral sensors coupled with government relaxation of regulations governing commercial use of UAVs, growers now have a new tool that has the potential to revolutionize farming by providing timely and cost effective imagery-derived vegetation indices (VIs) that can be used for N sidedressing. Imagery captured by UAVs offer higher spatial resolution, which allows for the removal of soil background and mixed pixels from pure vegetation pixels. Imagery with higher spatial resolution also allows for computer vision techniques to be applied to quantify the level of N stress in plants (Zermas et al., 2015).

UAV-based remote sensing application in N sidedressing is still in its infancy and research is needed to confirm its performance in the detection and quantification of N stress in corn so this technology can be deployed by growers and practitioners to improve in-season N management and NUE. The premise is that this technology is cloud cover resistant, and allows for flexible scheduling if farmers can overcome imagery processing, scalability and VI derivation. In this Chapter, we compare UAV derived Vegetation Indices (Vis) to well established proximal and remote crop sensing indices for in-season detection of corn N status.

The specific objectives of this study were to: 1) Compare the performance of UAV-based multispectral remote sensing to well-established SPAD chlorophyll meter sensing and Crop Circle Normalized Difference Vegetative Index (NDVI) for quantifying N status in corn at different growth stages and locations in Minnesota; and 2) Evaluate the accuracy of N sidedress fertilizer recommendations based on multispectral remote sensing collected with a UAV platform.

## Materials and Methods

This portion of the study was conducted at four different fields located in southern and southeastern MN (Figure 1) during the 2013 and 2014 growing seasons (four site-years). Janesville and Theilman were studied in 2013, while New Richland and St. Charles were studied in 2014. This region of the state is dominated by rainfed corn-soybean rotation producing the highest yields in the state. However, this region is also susceptible surface and ground water N pollution (MPCA, 2013). Janesville and New Richland fields are developed over lacustrine parent material. Cordova (mesic Typic Argiaquolls) and Le Sueur (mesic Aquic Argiudolls) are the two soil series in Janesville while a combination of Canisteo (mesic Typic Endoaquolls), Glencoe (mesic Cumulic Endoaquolls) and Webster (mesic Typic Endoaquolls) is present at New Richland. On the other hand, Theilman and St. Charles fields are formed on loess parent material dominated by silty loam texture with the Fayette (mesic Typic Hapludalfs) soil series at Theilman and Seaton (mesic Typic Hapludalfs) and Eitzen (mesic Mollic Udifluvents) series at St. Charles.

Fig.1: Four locations of the study in MN. Two locations (Janesville and New Richland) are in Waseca County, one is in Wabasha County (Theilman) and one is in Winona County (St Charles).

At each site, corn (Pioneer P9917) was planted following soybean and treatments were applied according to a randomized complete block design (RCB) with four replications. Treatment plots were 18 m x 6 m and row spacing was 0.76 m, resulting in eight rows per plot (only the central four rows were used for yield estimation). Timing and management practices for each field are summarized in Table 1. Two sub-treatment effects were represented in each block. The first sub-treatment effect is composed of seven pre-plant (PP) N rates varying between 0 and 210 kg/ha (treatments 1-7) at increments of 35 kg/ha. The second sub-treatment consisted of sidedressing (SD) N at V6 or V10 (Table 1). Agrotain treated urea was used as a source of N for sidedressing treatments.

Table 1: Sidedress N Fertilizer (kg/ha) Treatments at Janesville, New Richland, Theilman and St. Charles.

| Trt # | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 |
|---|---|---|---|---|---|---|---|---|---|
| PrePlant N | 35 | 35 | 70 | 70 | 35 | 35 | 70 | 70 | 0 |
| V6 N Sidedress | 70 | 105 | 35 | 70 | 0 | 0 | 0 | 0 | 0 |
| V10 N Sidedress | 0 | 0 | 0 | 0 | 70 | 105 | 35 | 70 | 0 |

All spectral data were converted to relative values by computing the ratio between spectral data for each observation and the treatment with the highest N rate (210 kg ha$^{-1}$) within each respective block (Table 1). This normalization aims to reduce block variability and reduce biomass impact (Zhou et al., 2018). After determining the EONR for each block, the dEONR was computed (Barker and Sawyer , 2010) for each plot as the difference between the block EONR and the applied PP N rate (Equation 2). A yield response ratio (YR) was also computed for each block based on the yield ratio between the zero N and highest PP N plots (Equation 3). This ratio was used to compare block response to N amendment within the same site.

$$\text{Deficit EONR (dEONR)} = \text{Applied N} - \text{EONR} \qquad \text{(Eq. 2)}$$

$$\text{Yield response index (YR)} = (\text{Yield (High N plot )})/(\text{Yield (Zero N plot)}) \qquad \text{(Eq. 3)}$$

## Aerial Image Acquisition

Aerial multispectral images were captured at 121 m altitude above ground level (~6.6 cm ground sampling distance) between 1000 and 1400 local time at each of three growth stages for each site-year (i.e., V6, V10, and R2) with a 6-band (blue, green (G), red (R), red-edge, near infrared (NIR) 1 and 2 bands) miniature multi-camera array system (Mini-MCA 6, MCA hereafter; Tetracam Inc., Chatsworth, CA, USA). The MCA (700 g) was mounted on an octocopter (MikroKopter Okto XL; Foersom Engineering Solutions, Luxembourg) UAV with dimensions of 73 cm (L) x 73 cm (W) x 36 cm (H) and maximum payload of 2,500 g. The UAV had propellers with a 30 cm diameter and was powered by two 4S 14.8V (5000 mAh) Lithium-Polymer batteries. The MCA contains an array of six factory-aligned CMOS image sensors (1280 x 1024 pixels; pixel size 5.2 cm), each with its own lens (9.6 mm focal length) and interchangeable narrowband band-pass filters that only allow light energy to be transmitted within a specific wavelength range to be captured by its sensor.

Images were captured with the MCA system using exposure times between 4 ms and 7 ms (using the auto-exposure setting) and saved at a 10-bit dynamic range. Images captured for each sensor in the MCA were stored on 2 gigabyte compact flash cards in RAW format. The PixelWrench2 software (version 1.2.2.9; Tetracam Inc., Chatsworth, CA, USA) was used to convert RAW images into multiband TIF format. Examination of the multispectral imagery revealed that band 5 (NIR 800nm) was saturated for all collection periods and therefore band 6 (NIR 900nm) was used for NIR reflectance.

## Aerial Imaging Pre-Processing

### Radiometric correction:
A Teflon calibration tag (36% reflectance; product# TTC1034) was imaged at the beginning of each flight mission and used to convert digital numbers to reflectance similar to the method used by Walczykowski et al. (2014) and Peddle et al. (2001).

### Georeferencing and band registration:
After the radiometric correction, multi spectral imagery was georeferenced using ESRI ArcMap 10.3 and the Georeferencing toolset. Four ground control points with GPS coordinates were used to georeferenced each scene. Each band was georeferenced separately to produce a better alignment and registration of the six bands in each scene. This improves pixel to pixel alignment for the purpose of estimating vegetative indices.

### Spectral data extraction:
Average spectral response of each plot was extracted from each raster image by block as each block was captured in a separate scene. This technique allows the block error term of the RCB to include errors related to changes in the remote sensing system and environment from scene to scene that are not due to the N treatment. First, single band rasters

were cropped using a buffered shapefile for the plots leaving one meter buffer area around each plot boundary. Then tabular data for each band (average per plot) was extracted using ArcMap's Zonal Statistics from the Spatial Analyst toolset. These data were used to compute the different VIs.

Vegetation index computation: The objective of this first study protocol is not to develop threshold values for sidedressing but rather to compare the performance of UAV-derived spectral vegetation indices with the well-established techniques including SPAD, and Crop Circle indices for prediction of N status in corn. During this process, absolute spectral measures are converted to relative measures based on a normalization using the high N plot within each block similar to the method developed by Schepers et al. (1992) and Peterson et al. (1993). It is these relative measures that are used as a response rather than absolute spectral indices.

First, absolute VIs were computed based on extracted plot averages for each of the six multispectral bands before converting them to relative values (Equation 4). In this expression, NDVI stands for Normalized Difference Vegetation Index (NIR-R)/(NIR+R), GRVI stands for Green Vegetation Index (G – R)/(G + R), GNDVI stands for Green Normalized Difference Vegetation Index (NIR-G)/(NIR+G), and GDVI stands for Green Difference Vegetation Index (NIR-G). This approach has been suggested for reducing differences in response related to field patterns, and it has been successfully adopted for SPAD reading (Schepers et al., 1992; Varvel et al., 1997; Barker and Sawyer, 2010), and for spectral indices (Biggs et al., 2002;, Barker and Sawyer, 2012; Tremblay et al., 2011).

Researchers suggested relative response to reduce variation due to differences related to soils, hybrids, population densities, and growth stages and conditions (Schepers et al., 1992), thus allowing comparison between different sets of data that otherwise would not be possible. Normalizing absolute values in each block by the corresponding N rich value does two important things. First it highlights and stretches the difference between the different treatments that is due to N, and it allows comparison of results from different blocks, locations and growth stages. In this study, block level analyses provide an additional advantage of reducing the experimental error related to the acquisition of multispectral data with the UAV since each block was captured in an image individually. In the case of a simple ratio vegetation index, such as the GRVI, if the relationship between digital numbers and the reflectance is assumed to have a zero intercept for both the NIR and green bands, then converting absolute GRVI to relative GRVI (rGRVI) within each block would negate the need to convert the digital numbers to reflectance. This simplification is due to the fact that the slope of conversion line for both green and NIR bands cancels out during the normalization process. This within-block conversion of absolute response to a relative spectral measure would be similar to using a reference strip (N rich area) within each management zone in a field for normalization and thus for developing N sidedressing. This technique has been shown to improve remote sensing-based N sidedressing for corn (Roberts et al., 2012).

$$\text{Relative index (rSPAD, rNDVI, rGRVI, rGNDVI, rGDVI)} = \text{(value (trt))/(Block value (High N plot) )} \qquad \text{(Eq. 4)}$$

Where rSPAD is the relative SPAD, rNDVI is the relative NDVI, rGNDVI is the relative GNDVI, rGRVI is the relative GRVI and rGDVI is the relative GDVI. All these indices were computed at the block level.

### Effectiveness of UAV based N Sidedress Applications

We used plots 8-11 for V6 and 12-15 for V10 to study the performance of UAV-based sidedressing at both growth stages and to compare a block specific method to a regional based method. We examined individual plots to determine those for which the amount of N that was sidedressed (35 or 70 kg/ha) was equivalent to the sidedressing rate that would be computed based on the two different techniques. The first technique relies on a block level quadratic plateau (QP) algorithm comparing the efficacy of rGRVI, rNDVI, rGNDVI, rGDVI to that of rSPAD. This method represents a block-specific N sidedressing algorithm equivalent to using an N rich strip per management zone in the field. The regression equation relates relative spectral measures to the dEONR, thus suggesting how much N sidedress would be needed for each plot to spectrally resemble the block high N plot while taking into account the block EONR. The EONR was computed based on block yield response to N. The equations used to compute the dEONR (sidedress) are presented in Tables 8 and 9 by growth stage, vegetation index, location and block. The second technique is based also on the quadratic fit using V10 rGRVI but combining data from all blocks and locations in lieu of developing the relationship between relative indices and dOENR by block (equation 7). This second method represents a regional algorithm using spectral response data from different fields and seasons. We defined the effectiveness of sidedressing for a given plot as reaching the same yield as the corresponding block EONR. We used yield values of the two treatments sandwiching the EONR in each block to compare yields. This is a realistic approach given that in field situations, as-applied application rates always differ from the prescription rates by as much as 10 kg/ha (Fulton, 2003).

### Statistical Analysis

Regression analyses, ANOVA and ANCOVA were conducted using R software to investigate the impact of PP N treatment on yield (Snedecor and Cochran, 1989). The ANOVA error term was computed for each treatment by subtracting the average of four replications (Bhatti et al., 1991; Mamo et al., 2003). Pearson correlation was used to evaluate the strength of the relationship between UAV-derived indices and SPAD and Crop Circle indices within each block. Quadratic plateau regression was used to evaluate the relationship between PP N and the different spectral indices.

## Results

### Economically Optimum Nitrogen Rate (EONR) and Maize Yields

Nitrogen yield response using a quadratic fit with plateau (Cerrato and Blackmer, 1990) allowed estimation of the EONR using a 0.06 price ratio for kg of N to a quintal of corn produced. EONR values for Block 1 at Theilman were excluded from further analysis due to waterlogged soil. Table 2 shows that the locations with finer textures (Janesville and New Richland) had smaller

EONR (134 and 152 kg N/ha) compared to EONR values (179 and 181 kg N/ha) at the coarser textured locations (Theilman and St. Charles). Nitrogen losses by leaching were most likely larger in coarser soils than finer soils, leading to larger EONR values. Average soil organic matter (SOM) contents were larger (5.2 and 6.8%) at Janesville and New Richland than at Theilman (3.2%) and St. Charles (3.1%). The smaller SOM contents on coarser textured soils likely had smaller mineralized soil N than on the finer textured soils, leading to larger EONR values.

Very strong correlations (0.88 to 0.91) were observed between pre-plant N fertilizer rate and maize yield (Table 2), indicating a strong yield response to applied N at all four locations. Maize yields at EONR (Table 2) were largest at Janesville (12.0 t/ha) and St. Charles (12.1 t/ha), and smallest at Theilman (10.1 t/ha) and New Richland (10.0 t/ha). Rainfall was average in 2013 and the finer textured soil location (Janesville) produced higher corn yield than the coarser texture soil location (Theilman). Conversely, in 2014, the coarser textured soil location (St. Charles) produced the highest yield. However, the 2014 growing season was exceptionally wet and it seems that under these conditions soils with lower SOM content are able to overcome excessive moisture likely due to better internal drainage. New Richland had very uneven precipitation across the growing season, in comparison with the other three locations, causing relatively low crop yields.

Table 2: Economically Optimum Nitrogen Rate (EONR), Yield at EONR (YEONR) and Pearson Correlations Between Pre-Plant N (PPN) and Yield for the Four Blocks (B) in Each of the Four Locations of this Study.

| **Locations** | **EONR in kg ha$^{-1}$ / Yield (YEONR) in t ha$^{-1}$** | | | | **coefficient of determination $R^2$ for PP N with yield** | | | |
|---|---|---|---|---|---|---|---|---|
| | **B1** | **B2** | **B3** | **B4** | **B1** | **B2** | **B3** | **B4** |
| **Janesville (2013)** | 144.5<br>12.0 | 155.7<br>12.1 | 119.8<br>12.2 | 115.5<br>11.6 | 0.91 | 0.93 | 0.87 | 0.91 |
| **Theilman (2013)** | 40.5<br>8.5 | 182.5<br>11.1 | 201.5<br>11.6 | 152.3<br>9.2 | 0.23 | 0.90 | 0.91 | 0.93 |
| **St. Charles (2014)** | 168<br>11.1 | 169<br>11.6 | 201.5<br>13.5 | 186<br>12.2 | 0.91 | 0.89 | 0.87 | 0.85 |
| **New Richland (2014** | 153.5<br>9.0 | 153.5<br>10.4 | 161.5<br>10.9 | 140<br>9.8 | 0.85 | 0.93 | 0.93 | 0.89 |

## Accuracy of Crop Yield Predictions with UAV Based Tetracam Remote Sensing

Green difference vegetation index (GDVI) values were an accurate predictor of final yield at each growth stage and experimental site (Table 3), especially for growth stages V10 and R2.

Yield predictions using GDVI values were moderately good at growth stage V6, when canopy closure was often not achieved.

Table 3: Correlation between Green Difference Vegetation Index (GDVI) values and final crop yield at four Minnesota sites for the V6, V10 and R2 growth stages.

| Location | GDVI V6 | GDVI V10 | GDVI R2 |
|---|---|---|---|
| Janesville 2013 | 0.85 | 0.76 | 0.85 |
| Theilman 2013 | 0.56 | 0.69 | 0.83 |
| St. Charles 2014 | 0.67 | 0.79 | 0.70 |
| New Richland 2014 | 0.51 | 0.73 | 0.78 |

## Accuracy of N Deficiency Assessment with SPAD Chlorophyll Meter, CropCircle and UAV Tetracam

Strong agreement existed in quantification of N deficiencies with UAV-derived vegetation indices and pre-plant N fertilizer application rates (Table 4) across all three growth stages and each study location. At V6 corn growth stage, SPAD chlorophyll meter readings were equally efficient at quantifying corn N status ($R^2$ = 0.75) relative to UAV-derived indices GRVI (0.77), GNDVI (0.72) and to a lower extent NDVI (0.69) and GDVI (0.66). Crop Circle NDVI was also highly correlated with SPAD readings at this growth stage with correlation values of 0.85, 0.79, 0.78 and 0.77 for NDVI, GNDVI, GRVI and GDVI, respectively. On the other hand, at V10 growth stage, the SPAD chlorophyll meter outperformed UAV-derived indices in the strength of the relationship between N deficiency and PP applied N with a coefficient of determination of 0.84. Among UAV-derived indices at this growth stage the GNDVI ($R^2$= 0.75) and GRVI (0.74) were very similar and slightly better than the GDVI (0.69) and the NDVI (0.63). At V10, Crop Circle GNDVI ($R^2$= 0.85) and GRVI ($R^2$= 0.84) were more strongly correlated with SPAD than with GDVI (0.78) or NDVI (0.74). The same trend was observed at R2 corn growth stage where SPAD has the strongest relationship with PP applied N ($R^2$= 0.89) followed by Crop Circle indices GNVDI ($R^2$ =0.79), the GDVI ($R^2$= 0.76), the GRVI ($R^2$= 0.75) and lastly the NDVI ($R^2$= 0.61). UAV indices were also highly correlated with SPAD at this growth stage, with correlation values of 0.77, 0.76, 0.75 and 0.75 for the GNDVI, NDVI, GRVI and GDVI respectively.

Overall, the ability of UAV spectral indices to detect and quantify corn N status improved or was stable over time, except with NDVI that weakened slightly over time, confirming the reported midseason saturation of NDVI (Hill, 1998; Shanahan et al., 2008; Baret and Guyot, 1991). Overall, UAV-based indices agreed with SPAD chlorophyll meter and Crop Circle, with indices combining the NIR and green reflectance such as GRVI and GNDVI outperforming the ubiquitous NDVI.

Table 4: Temporal changes in the coefficient of determination between SPAD meter readings and UAV or Crop Circle derived maize vegetation indices at three growth stages.

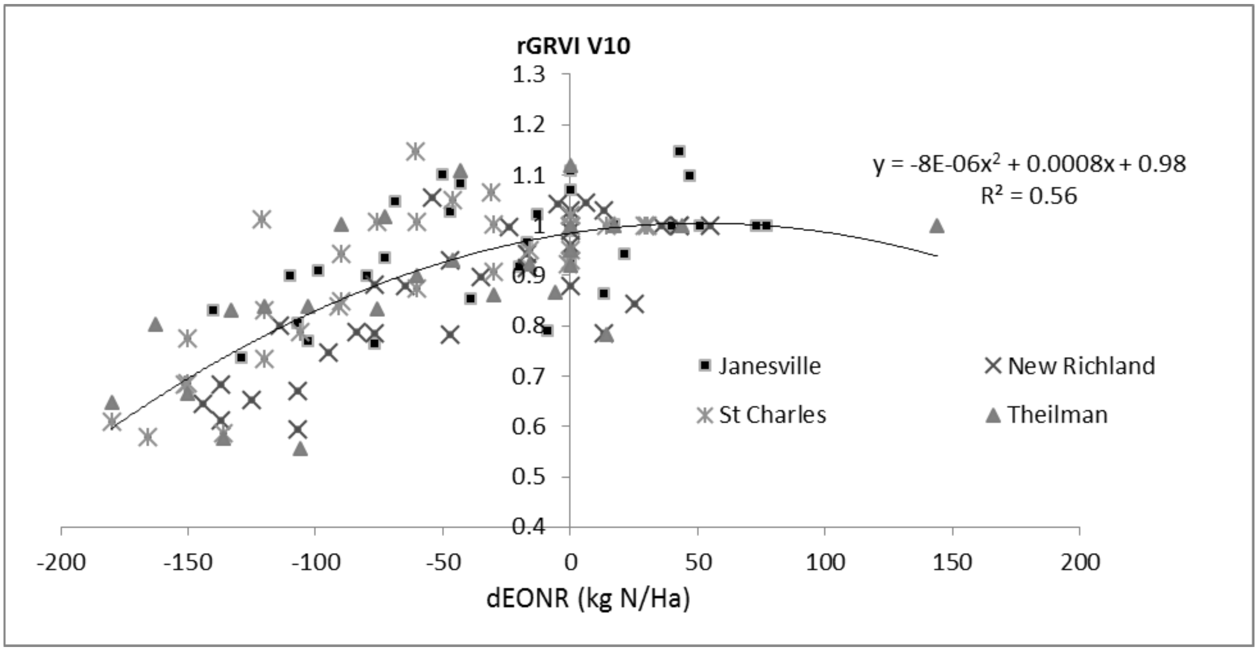
| Growth stages | GNDVI | NDVI | GRVI | GDVI |
|---|---|---|---|---|
| | UAV Based Vegetation Indices | | | |

| | | | | |
|---|---|---|---|---|
| V6 | 0.72 | 0.69 | 0.77 | 0.66 |
| V10 | 0.75 | 0.63 | 0.74 | 0.69 |
| R2 | 0.77 | 0.76 | 0.75 | 0.75 |
| | Crop Circle Based Vegetation Indices | | | |
| V6 | 0.79 | 0.85 | 0.78 | 0.77 |
| V10 | 0.85 | 0.74 | 0.84 | 0.78 |
| R2 | 0.79 | 0.61 | 0.75 | 0.76 |

This agreement is in the realm of values published in the literature. For instance, Tremblay et al. (2014) reported an $R^2$ value of 0.67 between UAV-derived spectral indices (TCARI/OSAVI) and SPAD for corn at V6 growth stage using a similar multispectral sensor in Canada. Similarly, Zaman-Allah et al. (2015) compared UAV-derived NDVI to ground-based NDVI for corn and wheat during productive growth stages and found a correlation value of 0.83 similar to our UAV-derived indices (GNDVI and GRVI) and SPAD correlation at V10 growth stage. The magnitude of the relationship between SPAD and UAV-derived indices in our study is also comparable with that of ground-based optical sensing and SPAD reported in the literature. For example, Sudduth et al. (2010) reported an $R^2$ value of 0.73 between SPAD and Crop Circle NDVI, and 0.70 for SPAD and GreenSeeker NDVI. These comparisons show that UAV-based sensing is comparable to ground-based sensing. UAV-derived indices however do not involve ground sampling, as the entire plot is sensed and averaged, thus eliminating the sampling error that comes when using SPAD. This can be an advantage in agricultural fields when there is significant micro heterogeneity that can render SPAD sampling ineffective. The same can be said about proximal optical sensors such as Crop Circle, RapidScan or Greenseeker, as deploying them in the field often involves ground sampling, and therefore, adds a sampling error that is avoided with UAV-based sensing.

## Assessing Crop N Requirements using GRVI and NDVI

GRVI outperformed the NDVI explaining corn N requirements regardless of growth stage. Plotting the rGRVI for each treatment against its corresponding block derived dEONR shows that the quadratic fit captures 46% of the variability when data from all locations and growth stages were aggregated, compared to only 35% when using the rNDVI. This superiority of the rGRVI was growth stage resistant. In fact, the coefficient of determination increased for rGRVI from 0.46 when growth stages were combined to 0.50 and 0.56 for V6 and V10 growth stages respectively (Figure 2), while no improvements were observed for rNDVI. More important in these figures, however, is the slope of the fit near N sufficiency. In order for any index to be efficient at making an N sidedress rate recommendation, it needs to be able to discriminate between crops showing little or no N deficiency. In this study, these near sufficiency crops are represented by N deficiency levels (Difference with the EONR) between zero and 50kg/ha.



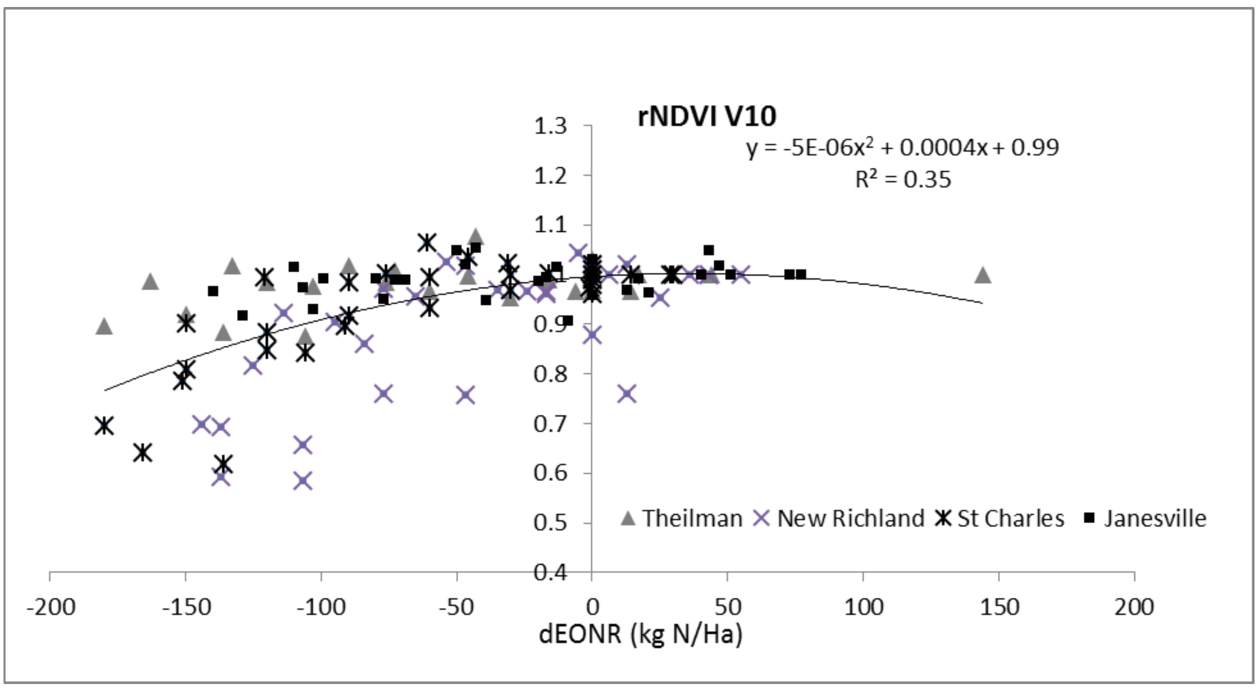




Fig. 2: Relationship between dEONR and rGRVI (top) or between dEONR and rNDVI (bottom) at growth stage V10 combining data from all sampling dates and sites.

From Figure 2, it is clear that the rGRVI does a better job than the rNDVI in discriminating between plots with different N stress levels especially in the dEONR range between 0 t0 50 kg/ha (values range between 0.95 and 1 for rGRVI vs 0.99 to 1 for rNDVI). This early saturation in the rNDVI with regard to N stress makes it unfit for detection of slightly stressed corn plant at the time of SD based on this spatiotemporal aggregated data. The fit of measured dEONR data to the regression curve was worst for the New Richland site, which had the highest

SOM levels. This indicates that it is more accurate to use rGRVI to estimate N fertilizer requirements at locations with lower SOM levels (and less soil N mineralization).

Block derived N sidedressing rates computed based on comparing plot rGRVI values with the corresponding block EONR resulted in an accuracy of 75% (n=32 plots) when UAV sensing data from V6 and V10 growth stages were combined to develop the quadratic equation. GRVI was used for this comparison based on its good overall performance compared to other indices, while being a simple ratio to compute. Accuracy for a given plot is defined as statistically reaching the optimum yield achieved with the EONR of the corresponding block. This accuracy was improved to 80% (n=14) at the V10 growth stage compared to only 70% (n=18) at V6. This improved efficacy at V10 is likely attributed to improved prediction of N status, chlorophyll content and grain yield using remote sensing post V6 as reported in other studies (Dias Paiao, 2016; Teal et al., 2006; Tremblay et al., 2014 ). In fact, early season (V6 and earlier) plant uptake rate of N is low compared to later in the season. Ma et al. (1999) reported that less than 20% of total N uptake in maize occurs before V6. Overall, sidedressing based on this block-derived approach reduced N amount applied by 21% as compared to the PP EONR application (n=32 plots). This estimate was computed based on comparison between block EONR values and the remote sensing derived rates for plots that reached the EONR yield.

Scharf et al. (2011) reported a similar reduction (25%) of N fertilizer load using ground-based active sensors. Likewise, Raun et al. (2002) reported a 15% improvement in NUE for cereals following the adoption of sidedressing based on handheld optical sensing. This improved N use efficiency using remote sensing-based sidedressing has been touted as a selling point for sidedressing, and we confirm it here in this study using UAV based spectral indices. We used the same aforementioned technique with SPAD for a benchmark comparison. SPAD-based sidedressing efficacy at V10 was slightly better than GRVI reaching 87% (n=16 plots), while reducing the N load by the same percentage (21%).

## Conclusions

In Minnesota, there is a need for nitrogen management strategies that reduce nitrogen fertilizer pollution, improve nitrogen use efficiency and therefore growers' return on investment. Recent advances in both unmanned aerial vehicle (UAV) platforms and multispectral sensors, coupled with the recent flexibility in regulations governing commercial use of UAVs are helping accelerate interest in UAV-based in-season variable rate nitrogen management strategies to reach these goals. Corn was grown in four fields in southern Minnesota (Janesville, New Richland, Theilman and St. Charles) using a randomized complete block design. An octocopter equipped with a Tetracam Mini-Multiple Camera Array system was used to capture aerial imagery at three corn growth stages (V6, V10, R2). Vegetation indices computed from UAV/multispectral imagery were compared to SPAD chlorophyll readings and ground-based CropCircle optical measurements. UAV–derived indices coupled with estimates of economically optimum nitrogen rates (EONRs) were used to quantify in-season corn nitrogen stress and to compare sidedress efficacy of regional based nitrogen recommendations. Higher EONRs were observed at coarser-textured soil locations with lower soil organic matter. Green difference vegetation index (GDVI) values were an accurate predictor of final yield at each growth stage and experimental site, especially for growth stages V10 and R2. UAV-derived block-normalized green ratio vegetation index (GRVI) and green normalized difference vegetation index (GNDVI) were strongly correlated with SPAD and CropCircle indices in estimating corn nitrogen status. Nitrogen sidedressing based on V10 block specific differential EONR (dEONR) had efficacies of 87%, 80% and 71% for SPAD, UAV/GRVI and UAV/GNDVI respectively compared to pre-plant EONR application. Thus, site specific N recommendation algorithms outperformed the combined-fields algorithm (55% efficacy). Sidedress N based on multispectral GRVI reduced nitrogen fertilizer use by 21% compared to the EONR, without impacting yield.

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# Chapter 2: Agronomic, Environmental and Economic Impact of Variable Rate Nitrogen on Rainfed Maize in a Typical Glacial-Till Field in Minnesota

## Introduction

Offsite movement of agricultural nitrogen is a major concern to society in Minnesota (Gourevitch et al., 2018; Keeler et al., 2016) as nitrogen is very expensive to remove from water, a shared resource. The unintended movement of nitrogen from agricultural landscapes has significant environmental, agronomic and economic adverse effects. For instance, the majority of nitrate pollution of the shallow aquifer is attributed to agricultural activities (Cassman et al., 2002), causing a major drinking water health concern in rural areas (Walton 1951; US EPA 1991; Keeler and Polasky, 2014; Warner and Ayotte, 2014). Agricultural nitrate from the Upper Mississippi is also a major cause for the increasingly frequent and significant hypoxia events (Turner and Rabalais, 1991; Turner et al., 2006; Selman et al., 2008; Boesch et al., 2009), and lake eutrophication and the subsequent loss of recreation (Conley et al. 2009). Lastly, mismanaged agricultural nitrogen can escape to the troposphere via nitrous oxide emissions, contributing to global warming (Shcherbak et al., 2014).

Because of the various ways nitrogen can leave agricultural landscapes (runoff, leaching, denitrification and volatilization), it is often referred to as the elusive element. This makes it difficult for cereal crops like maize, which have high N requirements and are not capable of atmospheric nitrogen fixation, to be efficient nitrogen scavengers. As a result, cereals N use efficiency (NUE) is only 33% to 50% (Raun and Johnson 1999; Cassman, 2002; Kitchen et al., 2008; Raun and Schepers, 2008) illustrating the significant loss that agricultural N undergoes. Growers in Minnesota are therefore facing a dilemma of applying sufficient N fertilizer to sustain optimum maize yield, as well as their bottom line, while reducing the impact of N on the environment. Site specific nutrient management (SSNM), such as variable rate nitrogen, (VRN) is one management strategys that can reduce off-site movement of N from agricultural land by spatially and temporally matching crop requirement and nutrients amendment (Roberts et al., 2012). This is accomplished by mapping within-field variability using either Grid or MZ approaches (Khosla et al., 2002), with management zones (Mulla, 1991) gaining popularity (AgVise publication stats) due to its lower cost of execution.

For further improvements in N management, delaying N application is recommended, which is usually achieved by sidedressing. Sidedress (SD) can be based on a split of the Economically Optimum Nitrogen Rate (EONR). In this strategy, a portion of N is applied at or before planting and the remaining sidedressed around V6-V10 maize growth stage based on information provided by crop models or remote sensing. An example of remote sensing approaches is the N reference method based on in-season sensing. This technique was found to improve N management on cereals (Schepers et al., 1992; Raun et al., 2002; Hatfield et al., 2008), although recent research found that estimating in-season N requirement continues to be a challenge for the scientific community (Morris et al., 2018).

Roberts 2011 suggested combining this N reference technique with management zones for improved N management. This can be accomplished by having an N reference strip or plots for each homogeneous zone of the field to better capture N dynamics and to account for different mineralization potential in each zone of the field. Most VRN research was either plot-scale research or focused solely on yield as response for assessing the benefit of VRN. Therefore, there is a need for field-scale research to assess VRN impact not only on yield, but also on profitability and environmental quality.

The overall objective of this two-year, field-scale research is to: 1) Assess the agronomic, economic and environmental impacts of in-season VRN compared to conventional N management. The conventional N management is based on uniform application of N based on the University of Minnesota Extension recommended EONR, while the VRN strategy is based on a management zone approach with corresponding N reference plots for each management zone.

# Materials and Methods

## Site Description

The study site is located in southern Minnesota at the University of Minnesota Southern Research and Outreach Center, in Waseca, Minnesota (Figure 3). A 16-hectare field divided into nine subfields (0.8-2.4 ha in size each) was planted with a maize (*Zea mays* L.) hybrid (Pioneer P0157AMX) during the 2016 and 2017 growing seasons, with a seeding density of 85,000 seeds $ha^{-1}$. Soybean (*Glycine max* L.) preceded the study in the 2015 growing season. Major soil types in this field are the Webster silty clay loam (fine-loamy, mixed, superactive, mesic Typic Endoaquolls) and the Nicollet clay loam (fine-loamy, mixed, superactive, mesic Aquic Hapludolls). The field is characterized by gentle slopes (1 to 3%). The soils and topography at this site are typical for glacial-till dominated landscape in Minnesota. Each of the nine subfields in this site is equipped with an independent subsurface drainage system.

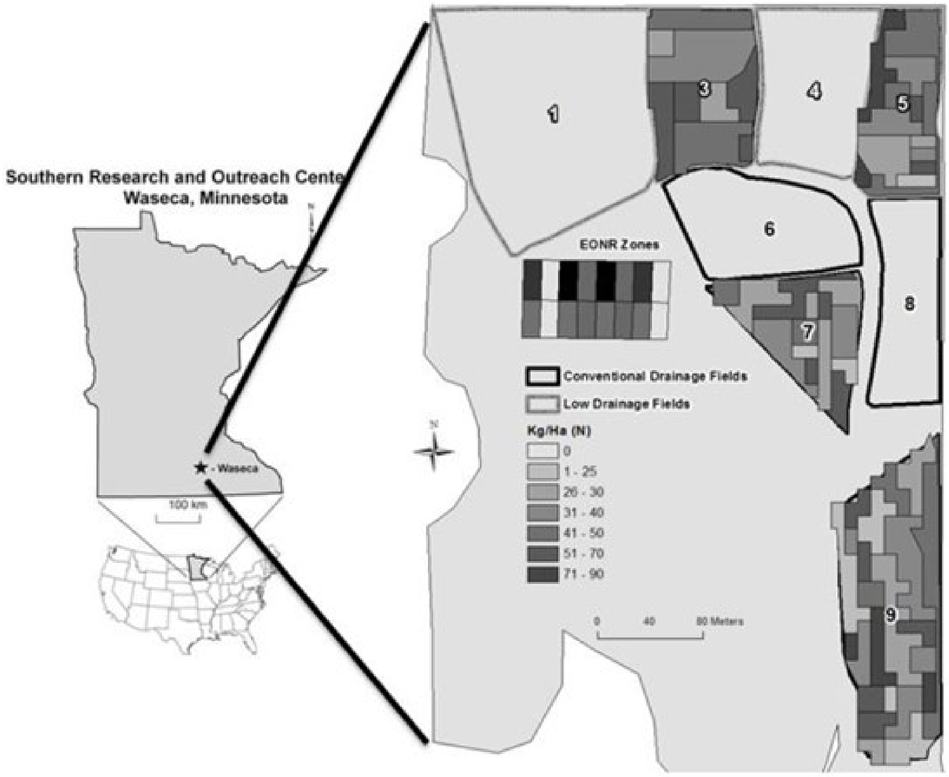


Fig. 3: Study location and design. The EONR zones are within Subfield #2, and they are used to develop the VRN recommendation for Subfields 3, 5, 7 and 9. N rates displayed are based on 2016 growing season results.

## Subfields classification/zoning

Four of the nine subfields were used as a control where the conventional uniform rate of nitrogen was applied at or before planting. The conventional nitrogen treatment consisted of applying the EONR (151 kg ha$^{-1}$ in 2016 after soybean, 202 kg ha$^{-1}$ in 2017 after maize, and 222 kg ha$^{-1}$ after soybeans in 2019). Four different subfields were used for the variable rate nitrogen (VRN) treatment consisting of a pre-planting rate of 1/3 of the EONR and the remaining applied at growth stage V7. The ninth subfield (Subfield #2) was divided into two management zones (blocks) based on topography, soil organic matter (OM) and previous yield data. These two zones represent the shoulder/backslope landscape position zone (High N response zone) and a footslope/toeslope landscape position zone (Low N response zone). The eight subfields were also classified, at a 10m cell size level, into these two zones using a supervised classification in ArcGIS (Maximum likelihood). Slope and the topographic wetness index (TWI) derived from Lidar data, electric conductivity (EC) mapped using the EM38-MK2 instrument, and normalized multi-year yield data were converted into a 10m cell raster format and used for the supervised classification. The classification was based on similarity between each 10m raster cell in the field and zone 1 and zone 2 from subfield#2. The outcome of this classification is a binary raster of 10m cell size with two classes.

## Nitrogen sidedress rate computation

Each of the two zones (blocks) within Subfield #2 was used for nitrogen reference plots (Plots are 15m by 40 m each) with four replicated pre-plant applied nitrogen rates (Napp) varying between 0 and the EONR. Nitrogen treatments in the response plots were applied before planting. In each of the three growing seasons, an optimal N rate (Nopt) was determined for each zone based on maize V6 active sensing with CropCircle ACS-210. CropCircle spectral data were collected using an All Terrain Vehicle (ATV), providing near infrared (NIR) and visible readings that were converted to the green normalized vegetation index (GNDVI = (NIR-G)/(NIR+G)).

In each growing season, the Nopt for each zone is determined as the N rate where further increases in N fertilizer rate do not increase GNDVI. The N sidedress rate is therefore computed based on the spectral difference between each 10m cell of the field and the highest GNDVI value of the corresponding zone. The assumption is that N rates used in developing the sidedress equation reach spectral saturation and that plots within each block(zone) are homogenous in terms of soil N supply or loss (between planting time and sensing time).

We used a quadratic model to relate GNDVI and the N deficit computed as the difference between Napp and Nopt (N deficit = Nopt - Napp) for each of the two zones. Raster map algebra in ArcGIS was used to implement the corresponding equation (based on zone classification) at the cell size level (10m) based on V6 GNDVI readings. These N sidedress rates were then adjusted to take into account the yield potential for each area of the field using yield data from the three previous corn growing seasons. The multi-year yield data were first cleaned and interpolated to 10m cell size, then normalized by dividing each year's yield data by the average yield of the field. The resulting raster had values varying between about 0.4 and 1.6. We instituted a minimum threshold of one for relative yield to avoid severe N deficiency as a result of low sidedress rate. The final sidedress rate is the product of the adjusted multiyear normalized yield and the GNDVI based rates.

To maintain consistency, urea was used as a source of nitrogen and was broadcasted at both application times; pre-plant (treated with urease inhibitor Agrotain) and sidedressing (untreated). A five-meter swath toolbar was used to spread urea in the nitrogen response reference plots (Figure 1) and for sidedressing the entire field, while a wider 10-meter swath spinner box was used to broadcast the pre-plant urea. A raven Viper Pro controller was used to apply the variable rate urea in the field. A John Deere combine fitted with a six-meter header and equipped with a yield monitor was calibrated and used for grain harvest. AgLeader SMS software was used to convert combine yield data files to a shapefile. Then using ArcGIS, we proceeded to clean yield data by removing the headland, double passes and outliers (based on three standard deviations from the mean). Outliers were also removed based on excessive moisture (moisture sensor errors). We used inverse distance weighting for interpolation given the high density of yield data and we selected a weighting exponent of four during the interpolation process (w=4) to give more weight to nearby points. The yield data were then resampled to a 10-meter surface raster before we applied a five meter buffer zone inside the boundary of each subfield to avoid edge contamination.

## Field Data Collection

Additional data were collected to facilitate the computation of the NUE and soil residual N (measured after harvest for potential leaching indication) in 2016 and 2017. NUE was not possible to calculate in 2019, because of loss of harvest time samples for grain and stover. All samples (soil, tissue and grain) were georeferenced to a horizontal accuracy of 2m. A total of 25 strategically chosen locations were routinely sampled for soil N, tissue N and S content, stover biomass and chlorophyll reading. Additionally, at harvest time, grain and stover N content were determined in all 25 sample locations. For soil residual N, immediately after harvest, soil samples (0-0.61m) were collected to measure the amount of nitrate N that remained in the field after the growing season. The georeferenced samples were used in surface interpolation using kriging or inverse distance weight when appropriate. One-meter spatial resolution four bands NAIP imagery (August 24$^{th}$ 2017) and five-meter spatial resolution five bands RapidEye imagery (August 23$^{rd}$, 2016) were used to derive vegetation indices that served as covariates in surface interpolation.

We evaluated the VRN treatment based on agronomic, environmental and economic metrics. Nitrogen Use Efficiency (NUE) and grain yield were used as metrics for the agronomic evaluation, while N rate applied and soil residual N were the metrics used for assessing the environmental impact of VRN. Soil residual N is thought of as a potential for N leaching. For assessing the economic impact of VRN we computed the profit increase and return on investment (ROI) following the adoption of VRN while accounting for the cost of VRN application. This cost was estimated based on fees charged by local crop consultants, although growers tend to bundle VRN with precision soil sampling, variable rate nutrients (P,K) and variable rate seeding. All statistics in this study were conducted using the R software (R project, 2017), while ArcGIS was used for spatial interpolation. An average metric for each subfield is computed using zonal statistics and clipping the corresponding metric raster by the buffered subfield boundaries.

Assessing yield response to nitrogen treatment is very complicated because yield is strongly influenced by the uncontrolled weather conditions of the growing season (strong inter-season variability). As a result, inter-seasonal weather variations can interfere with nitrogen treatment effect. For instance, weather impacts soil microbial activity and therefore soil organic nitrogen mineralization. Weather conditions also control nitrogen losses via leaching, denitrification and volatilization, thereby adding complexity. Inter-seasonal temperature differences can also impact maize plant development, controlling the length of both the vegetative and reproductive stages. This was evident in the 2016 growing season in Minnesota, which was one of the longest in historical records. Finally, inter-seasonal weather variation related to wind, ambient moisture, and temperature, affect evapotranspiration, and therefore, water movement in the plant and the subsequent nutrient uptake. To account for this weather interference, we converted the absolute grain yield of each subfield to a relative yield by normalizing the grain yield of each subfield by the average grain yield of the entire field (total of 8 subfields). This technique allows us to even out inter-seasonal weather influences on yield among control and treatment subfields, thus allowing both temporal (across years) and spatial (among subfields) comparisons. The impact of VRN is then assessed by evaluating the change in the normalized yield of each VRN subfield before and after VRN treatment.

For nitrogen use efficiency computation, there are different definitions and methods in the literature (Raun and Johnson, 1999). We used the definition that considers soil N contribution in the NUE. Using this method, SOM mineralization and spring available soil N are accounted for as sources of N uptake. This method is more accurate for describing NUE as it is less biased toward high OM soils. If soil N is ignored, as is the case for the NUE formula based solely on the ratio of crop removal and N fertilizer rate, high SOM soils will display high NUE values compared to low SOM soils for the same rate of N fertilizer.

To compute NUE, we first computed the amount of N recovered in both grain and stover and divided it by the amount of N that was applied. We used regression kriging to estimate the amount of N that was recovered in both grain and stover. Using the georeferenced stover and grain harvest samples (n=25) we developed a relationship between grain N export and grain yield, SOM and mid-season NDVI and GNDVI (based on NAIP imagery in 2017 and RapidEye imagery in 2016). The error term of this regression was interpolated by kriging and added to the regression estimate to generate a surface map for grain N export for the entire field. The same procedure was applied to generate a surface map for stover N for each subfield. To estimate the soil N contribution (without fertilizer), we first used regression to relate yield (with zero fertilizer) and EC as a continuous surrogate for SOM (n=6) and then we used ArcGIS to interpolate a surface map for soil N contribution based on EC. Lastly, for soil residual N, we applied regression kriging and interpolation using the 25 soil residual N georeferenced samples and the available continuous covariates.

## Drainmod Simulations of Nitrate Loss in Subsurface Tile Drains

Equations to predict nitrate-N load were developed based on simulated nitrate-N load for tile-drained fields in a corn-soybean rotation for different combinations of N fertilizer application timings and rates. The timings varied based on N fertilizer applied: 1) in the fall before planting corn (“fall”), 2) in the spring before planting corn (“spring”), and 3) as a split application, with half applied in the spring pre-plant, and the remaining applied as side-dress early in the growing season (“split”). Absent a comprehensive dataset of measured nitrate loads corresponding to each of these application timings, nitrate-N load data were obtained using the hydrologic model DRAINMOD-NII. The results of DRAINMOD-NII simulations were then used to develop regional predictive regression equations for nitrate-N losses based on climate and fertilizer management practices.

## Results and Discussion

The optimal N (Nopt) rate in 2016 was 100 kg ha$^{-1}$ for zone 1 and 152 kg ha$^{-1}$ for zone 2. Zone 1 rate was lower than the EONR of 151 kg ha$^{-1}$, which can be attributed to soil N contribution. In the previous growing season (2015 growing season) the field was planted to soybeans, and an early spring soil test revealed high levels of available nitrogen in the nitrate form which likely contributed to plant N uptake. In 2017 we decided to have three management zones instead of two. A third zone was generated by combing the GNDVI response from both blocks and assigning it to the flat areas of the field based on similarity and supervised classification. The optimal N rates in 2017 were 150, 180 and 200 kg ha$^{-1}$ for the three zones (Table 5). Using sidedress equations in Table 1, which relate GNDVI readings to the amount of N sidedress to be applied (N deficit), we developed VRN prescriptions compatible with a Raven controller and fertilizer spinner box.

Table 5: Sidedress N equations (kg ha$^{-1}$) for each management zone based on GNDVI at maize V6 growth stage.

| **VRN data** | **2016 growing season** | | **2017 growing season** | | |
|---|---|---|---|---|---|
| | **Zone 1 (Low Response)** | **Zone 2 (High Response)** | **Zone 1 (Low Response)** | **Zone 2 (Mid Response)** | **Zone 3 (High Response)** |
| **N deficit Equation** | $68692x^2 - 100871x + 37039$ | $y = -63520x^2 + 87236x - 29797$ | $793x^2 - 24552x + 1034$ | $-35241x^2 + 28745x - 5662$ | $10998x^2 - 11811x + 3168$ |
| **R square** | 0.54 | 0.87 | 0.87 | 0.85 | 0.65 |
| **$N_{opt}$ (kg ha$^{-1}$)** | 100 | 152 | 150 | 200 | 180 |
| **N bounds (kg ha$^{-1}$)** | 10-100 | 40-152 | 0-150 | 20-200 | 0-180 |

In 2019, optimal variable rate sidedress nitrogen rates were determined using spectral response to nitrogen. The "EONR" Python package (Nigon et al., 2019) was used to calculate the spectral response to nitrogen by fitting a quadratic-plateau function to observed green normalized difference vegetation index (GNDVI) spectral values. The modeled spectral response to nitrogen utilized spectral data from the small plot experiment for a range of preplant nitrogen rates (i.e., 0 to 222 kg ha$^{-1}$). The variable rate sidedress N treatments ranged from 42to 99 kg nitrogen ha$^{-1}$ in the VRN Subfields.

### Agronomic impacts

#### Grain yield

Yield increased significantly (Table 6) in this field between 2001 (8.13 t ha$^{-1}$) and 2017 (12.8 t ha$^{-1}$). This increase is likely due to better hybrid performance and overall improvement in agricultural management of the field. The yield increase over time is visible in all eight subfields (conventional and VRN). The decrease in 2019 yields was due to green snap crop damage. There is however no consistent ranking of the eight fields in terms of yield, which could be attributed to the variable impact of inter-seasonal weather conditions that interact with moisture availability and organic matter mineralization. It is likely that a growing season with abundant and well distributed precipitation (Tremblay et al., 2012) will result in less contrast between subfields when sufficient nitrogen is supplied.

Repeated-measures ANOVA applied to relative yields using three previous years of relative yield (2001, 2002 and 2004 are pre-treatment years) and three years of VRN (2016, 2017 and 2019 are post-treatment years) revealed no impact of VRN on yield. During the three-year period of the study, grain yield of VRN subfields was therefore statistically similar to that of conventional subfields, although VRN subfields received nearly 37% less nitrogen fertilizer.

Table 6: Corn grain yield and NUE for VRN and conventional subfields in Waseca, MN.

| Subfields | | Grain yield | | | | | | NUE | |
|---|---|---|---|---|---|---|---|---|---|
| | | **2001** | **2002** | **2004** | **2016** | **2017** | **2019** | **2016** | **2017** |
| **Uniform** | **1** | 1.03[a] (8.5)[b] | 1.02 (9.2) | 1.05 (11.1) | 1.03 (14.5) | 1.0 (12.7) | 1.02 (11.2) | 0.44 | 0.42 |
| | **4** | 1.02 (8.4) | 1.05 (9.5) | 1.02 (10.8) | 0.93 (13.1) | 1.02 (13.0) | 0.96 (10.6) | 0.36 | 0.44 |
| | **6** | 0.96 (8.0) | 0.97 (8.7) | 0.98 (10.3) | 0.95 (13.4) | 0.98 (12.5) | 0.98 (10.8) | 0.35 | 0.41 |
| | **8** | 1.02 (8.5) | 0.96 (8.6) | 0.93 (9.8) | 1.04 (14.7) | 1.05 (13.5) | 1.04 (11.4) | 0.38 | 0.38 |
| **Variable Rate** | **3** | 0.98 (8.2) | 1.03 (9.3) | 1.02 (10.8) | 0.99 (13.9) | 0.98 (12.5) | 0.98 (10.8) | 0.50 | 0.50 |
| | **5** | 1.07 (8.8) | 1.01 (9.1) | 1.04 (11.0) | 1.02 (14.4) | 1.01 (12.9) | 1.02 (11.3) | 0.48 | 0.48 |
| | **7** | 0.96 (8.0) | 0.97 (8.7) | 0.99 (10.5) | 1.01 (14.3) | 0.99 (12.6) | 1.02 (11.2) | 0.46 | 0.45 |
| | **9** | 0.98 (8.1) | 0.99 (8.9) | 0.98 (10.4) | 1.04 (14.7) | 0.97 (12.4) | 0.98 (10.8) | 0.49 | 0.47 |

(a) Relative yield of each subfield (normalized by the average). (b) Absolute yield value (t $ha^{-1}$)

## Nitrogen use efficiency

In the 2016 growing season, NUE varied between 35% and 44% for the conventional subfields and between 48% and 50% for the VRN subfields (Table 6). A similar variation was observed in the 2017 growing season. Overall, we see higher NUE for the VRN subfields (3, 5, 7 and 9) compared to the conventional subfields (1, 4, 6 and 8) both in 2016 (following soybean) and 2017 (following maize). In 2017, the conventional subfields showed higher NUE (except for Subfield #1) compared to 2016 which cannot be attributed to the higher N rates (2017 EONR = 202 kg $ha^{-1}$ versus 151 kg $ha^{-1}$ in 2016). However, this trend could be attributed to the lower yield, and therefore soil N contribution computed based on the zero N check plots. This observation was also corroborated by the lower spring soil N for 2017 compared to 2016.

Overall, VRN subfields showed consistently high NUE, which is likely due to the lower fertilizer rates as compared to the conventional subfields. Improving NUE for cereals is major concern for the society. It has tremendous implications in environmental protection and food security. From an environmental stand point, higher NUE is very desirable as it means less N is available to loss, while a lower fertilizer NUE can be an indication of insufficient uptake and thus potential loss and environmental pollution. On the other hand, from an agronomic stand point, a high NUE can indicate higher productivity (high removal) and/or an efficient use of fertilizer N, while a low NUE may be an indication of a stressed crop (biotic or abiotic), moisture deficiency or excessive leaching when N fertilizer has been applied. In this study we showed NUE values close to 50% in the VRN subfields. This a significant finding, with a potential to reduce the impact of cereal production on the environment. Not only we can produce cereals more efficiently but also in a way that is more environmentally friendly, because of the reduced losses that would otherwise enter the hydrosphere or troposphere.

## Environmental Impacts

One of the drivers for VRN adoption is its potential to reduce off-site movement of N to surface and ground water. To assess the impact of VRN on the environment in this study, we evaluated both soil residual N (immediately after harvest) and the amount of synthetic N fertilizer needed to achieve corn yield comparable to that of the EONR in the two growing seasons 2016 and 2017. Only the N fertilizer needs relative to EONR were estimated in 2019, due to budgetary limitations on residual soil N sampling and analysis.

### Nitrogen fertilizer load

According to Table 7, during the 2016 growing season, conventional subfields received an EONR rate of 151 kg ha$^{-1}$ of N (maize after soybean), while VRN subfields received on average 101 kg ha$^{-1}$ (33% less than the EONR). In 2017, the same conventional subfields received a higher EONR rate of 202 kg ha$^{-1}$ (second year of maize), while VRN subfields received between 140 and 164 kg ha$^{-1}$ (24% lower than EONR). In 2019, conventional subfields had an EONR rate of 188 kg ha$^{-1}$, compared with a VRN rate of 116 kg ha$^{-1}$ (37% lower than EONR). The VRN rates correspond to 64-71% of the EONR in 2016, 69-81% in 2017 and from 41-74% in 2019.

These rates translate into significant fertilizer load reductions on the VRN subfields compared to the conventional subfields that received the EONR. Between 43 and 54 kg ha$^{-1}$ of N was eliminated on the VRN subfields in the 2016 growing season, 38 to 62 kg ha$^{-1}$ of N was eliminated in the 2017 growing season, and 49 to 106 kg ha$^{-1}$ of N was eliminated in 2019 when compared to the EONR of conventional subfields. The basis for the N reduction achieved in the VRN subfields is accounting for spatial variability of soil sources of N, other than the synthetic fertilizer, that contribute to plant growth and development between planting time and sensing time (V6). Here we assumed that the zoning accounted for most of the spatial variability of soil N contribution or at least reduced it (within a zone).

Table 7: Synthetic N fertilizer load and soil residual N in VRN and conventional subfields.

| Subfields | | Fertilizer load (kg ha$^{-1}$) | | | Applied N (% of EONR) | | | EONR based Reduction (kg ha$^{-1}$) | | | Residual N (kg ha$^{-1}$) | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | **2016** | **2017** | **2019** | **2016** | **2017** | **2019** | **2016** | **2017** | **2019** | **2016** | **2017** |
| **Uniform** | **1** | 151 | 202 | 222 | 100 | 100 | 120 | 0 | 0 | 0 | 39 | 22 |
| | **4** | 151 | 202 | 222 | 100 | 100 | 120 | 0 | 0 | 0 | 43.2 | 23.5 |
| | **6** | 151 | 202 | 222 | 100 | 100 | 120 | 0 | 0 | 0 | 47.9 | 24.2 |
| | **8** | 151 | 202 | 222 | 100 | 100 | 120 | 0 | 0 | 0 | 52 | 26.4 |
| **Variable Rate** | **3** | 108 | 164 | 82 | 71 | 81 | 41 | 43 | 38 | 106 | 40.3 | 22.3 |
| | **5** | 101 | 140 | 122 | 67 | 69 | 65 | 50 | 62 | 56 | 45.7 | 24 |
| | **7** | 97 | 161 | 139 | 64 | 79 | 74 | 54 | 41 | 49 | 47.7 | 24.4 |
| | **9** | 98 | 149 | 122 | 65 | 74 | 65 | 53 | 53 | 56 | 45.5 | 23.5 |

### Soil residual nitrogen

Soil residual N represents a potential for N leaching since there is no more plant uptake. We found soil residual N to strongly relate to grain yield and EC (n=25). Regression kriging and ArcGIS zonal statistics were leveraged to compute the average soil residual N for each subfield. Our study shows higher soil residual N after the first year of maize, and less after the 2nd year, but to our surprise, there was no significant difference between the VRN and conventional subfields in term of residual N both in 2016 and 2017 growing seasons (Table 6). The lack of significant difference in soil residual N between VRN and conventional subfields despite the reduced rate of N fertilized used on VRN subfields and the indiscernible difference in grain yield could indicate significant N loss on the conventional subfields (i.e. leaching). This loss was confirmed in a concurrent study that showed significant nitrate leaching from the conventional subfields as compared to the VRN fields (Wilson et al., 2017).

Soil residual N was not related to applied N but positively to EC and negatively to the yield. This seems to indicate that later in the season, when N uptake is reduced, mineralization dominates the soil N pool, which may explain the strong relationship with EC. The lack of relationship between applied N and soil residual N would also explain the lack of significant difference between the VRN and conventional management in terms of soil residual N. But this does not explain the higher soil residual after the first year (maize after soybean) compared to the second year (maize after maize). One possible explanation for the higher residual after the first year of maize (second year after soybean) is a carryover of an improved SOM mineralization from soybean (low C/N ratio). The other possible explanation is the record long growing season of 2016, which could have mineralized more N.

## Economic impacts

Based on conversations with local independent crop consultants, a \$20 per hectare (\$8 per acre) service fee would cover the VRN protocol similar to the steps undertaken in this study. This includes delineation of three management zones, soil sampling with laboratory analysis for OM, in-season crop imagery (at -V6 maize growth stage) and VRN prescription and application. There is usually a premium charge of 8 dollars per hectare for variable rate dry fertilizer application (on top of the uniform application cost) by most ag service providers/cooperatives. The 20 dollars per hectare service fee includes also an 8 dollars per hectare charge for three-zone soil sampling and OM determination, 2 dollars per hectare for in-season vegetation index (which would be an alternative to CropCircle used in this study), and 2 dollars per hectare charge for writing the VRN prescription for the grower controller. This 20 dollars per hectare charge for VRN is, however, an over-estimation of the service fee, as the majority of growers bundle VRN with precision soil sampling of other nutrients (i.e. variable rate P, K and seeding), which brings down the cost of VRN.

Since we observed no significant difference in yield between the VRN and the conventional (EONR) subfields, the profitability (profit increase) is basically the fertilizer savings (at \$0.77/kg or \$0.35/lb for urea fertilizer) minus the VRN prescription cost. In this study, we see a significant and consistent profit increase in the VRN subfields that varied between 13 and 21 dollars per hectare in 2016, 9 to 28 dollars per hectare in 2017, and between 18 and 62 dollars per hectare in the 2019 growing season (Table 8). This profit increase corresponds to an ROI on the cost of VRN services amounting to 166-208% in 2016, 146-239% in 2017, and 216-408% in 2019. It is worth noting that the cost of VRN prescription and application is decreasing as more Ag technology startups, agricultural cooperatives and fertilizer dealerships are offering these services at discounted prices, especially with fertilizer purchase.

Table 8: Profit increase and ROI of VRN in two growing seasons.

| VRN Subfields | Profit increase and ROI | | |
|---|---|---|---|
| | **2016** | **2017** | **2019** |
| **3** | 13[a] (166%)[b] | 9 (146%) | 62 (408%) |
| **5** | 18 (192%) | 28 (239%) | 23 (216%) |
| **7** | 22 (208%) | 12 (158%) | 18 (189%) |
| **9** | 21 (204%) | 21 (204%) | 23 (216%) |

(a) Profit increase due to VRN (dollar per ha). (b) Return on investment of VRN

## Conclusions

A 16-hectare field in southern Minnesota divided into nine independent subfields was planted to maize in the 2016, 2017 and 2019 growing seasons. Four subfields received variable rate N based on V6 sensing and zone based optimal N computed using N management zone reference. VRN consisted of one third of the EONR applied at before planting and the remaining sidedressed at V7. Four subfields served as controls and received conventional pre-plant application of N based on the EONR. Repeated measures ANOVA using three previous years of normalized yield data for four VRN subfields showed no impact of VRN on yield, despite significant reductions in fertilizer rate (33%, 24% and 37% compared to the EONR in 2016, 2017 and 2019, respectively). VRN subfields displayed significantly and consistently higher Nitrogen Use Efficiency (NUE) values for the 2016 and 2017 growing seasons, with an average NUE of 48%. Finally, VRN for maize based on in-season sensing paid off every year, even in the absence of yield increases, because of the N savings that resulted from utilization of soil N.

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# Chapter 3: Effects of Fertilizer Timing and Variable Rate N on Nitrate-N Losses from Tile Drained Corn and Soybean Rotation at Waseca, MN Simulated Using Drainmod-NII

## Introduction

Nitrogen (N) originating from annual corn and soybean cropping systems in the Upper Mississippi river basin is a leading cause of impairment to both fresh and marine water systems (David et al. 2010, Schulte et al. 2006). Its role as a major contributor to one of the largest hypoxic zones in the world in the Gulf of Mexico (CENR 2010), has drawn intense scrutiny of N losses from agricultural lands in the Upper Midwest. Nitrogen movement from agricultural fields to waters predominately occurs in the highly water-soluble nitrate-N form, and its rapid movement to surface waters in the Upper Midwest is facilitated by the dense network of subsurface drainage systems in the region (Dinnes et al. 2002). It is estimated that nitrate-N entering the Mississippi River from upstream farm fields needs to decrease by at least 45% in order to reduce the extent of the hypoxic zone in the Gulf of Mexico (US EPA 2007).

The amount of nitrate-N moving from fields to waters is highly influenced by factors such as annual precipitation, mineralization of soil organic matter, and fertilizer management practices (Randall and Goss 2008). Nitrate loads exhibit a seasonal response, with the greatest amounts occurring during periods of little or no crop growth, when plant evapotranspiration and uptake of nitrogen are low (Randall et al. 2003). In the northern part of the Midwestern region where soils historically remain frozen through winter, the highest nitrate losses tend to occur during the months of April-June. In a 15 year study in Minnesota, this 3-month period accounted for 71% of the annual drainage volume and 73% of the annual nitrate loss from a corn-soybean rotation (Randall 2004).

Typical fertilizer management practices in the region may exacerbate potential N losses, placing excess N in the soil during the time of greatest loss potential. Large numbers of fields in southern Minnesota receive anhydrous ammonia fertilizer application during fall before planting (MPCA 2013), although there has been a significant shift towards urea applications in spring. Additionally, fields in the upper Midwest can display significant within-field variability in soil organic matter and nitrogen content (Mamo et al. 2003; Scharf et al. 2005), yet more than two-thirds receive blanket N application (Erickson and Widmar 2015), which can result in higher losses of N (Power et al. 2000). Nitrogen management practices which focus on applying the right rate of N at the right time, such as split and variable rate nitrogen (VRN), have been proposed as a practice which could reduce N loads to surface waters (i.e. Nelson 1985).

Split application of nitrogen fertilizer addresses the asynchrony in timing between nitrogen application and plant uptake by applying part of the total N amount at or before planting, and part as side-dress during the growing season. This approach delays full application of fertilizer until corn nitrogen uptake rates peak around growth stage V6-V8. An application strategy that utilizes this split timing, along with VRN addresses both the temporal and spatial mismatches between N application and crop development; VRN utilizes the same timing application strategy as the split application, but bases N fertilizer application rates on spatial variations in plant N requirements. VRN utilizes methods of estimating soil or plant N content to determine how much N should be applied at side-dress, potentially reducing the overall N applied. Side dressing rates can be variable based on crop sensing (Mulla 2013) or in-season modeling of plant available N.

There have been few studies on the effect of both timing and rate of fertilizer application on water quality. Here, we use the field-scale hydrologic simulation model Drainmod-NII to simulate the effect of fertilizer application rate and timing on nitrate loads from subsurface drainage over a 14 year period for rain-fed corn and soybean, at the Waseca Experiment Station, located in southern Minnesota. Field trials of split-VRN application at the site in 2016, 2017 and 2019 were used to validate model's performance for this practice, and inform the VRN application rates used in model simulation. Fertilizer rate and timing treatments simulated for the 14-year period included: 1) single application pre-plant (PP) using N rates based on Minnesota Extension recommendations; 2) split application of that N amount, with 50% applied pre-plant, and 50% applied as side-dress; and 3) a split-variable rate nitrogen (VRN) application, where the application was split 50/50 PP and side-dress, as well as using a reduced nitrogen rate based on optical sensor measurements of N need.

# Materials and Methods

## Experimental Site Characteristics

The study site is located in southern Minnesota at the University of Minnesota Southern Research and Outreach Center, at Waseca, Minnesota. The drainage experiment site at Waseca consists of nine plots ranging in size from 0.8 to 2.4ha. Plots 1-5 have drainage intensities of 13 mm $d^{-1}$ (conventional or "low" intensity), while plots 6-9 have a higher drainage rate of 51 mm $d^{-1}$ (high intensity) (Figure 4). The different drainage intensities were achieved using different combinations of drain depth and spacing, and were calculated using the Hooghoudt equation. For drains with a 1.2 m depth, drain spacing's are 12 and 24 m for the 1.2 m depth, while for a 0.9 m depth spacing's are 9 and 18 m for the 0.9 m depth. Each treatment of similar drain depth/spacing/drainage intensity has 1 or 2 replicate plots. More detail on the drainage design can be found in Sands et al. 2008.

Soils and topography found at the site are typical for south-central Minnesota. The major soil types at the site include Webster silty clay loam (fine-loamy, mixed, superactive, mesic Typic Endoaquolls) and Nicollet clay loam (fine-loamy, mixed, superactive, mesic Aquic Hapludolls). Average annual precipitation is approximately 889 mm; precipitation during the growing season (May through September) is approximately 533 mm (averages are the 30 year normal, 1982-2010). Plots were outfitted with tipping buckets to provide a continuous measurement of subsurface drainage flow rates for the years 2003-2008. Nitrogen concentrations were recorded on an event basis for the years 2003 to 2008. Nitrogen load data for the years 2003-2008 set was estimated using the Army Corps of Engineers model, FLUX, using the daily flow and sampled nitrogen concentration measurements. In 2016, 2017 and 2019, nitrate concentration was recorded as a grab sample on a weekly basis. In 2017 and 2019, instantaneous flow measurements collected at the time of concentration sampling were used to generate an estimate of the daily load.

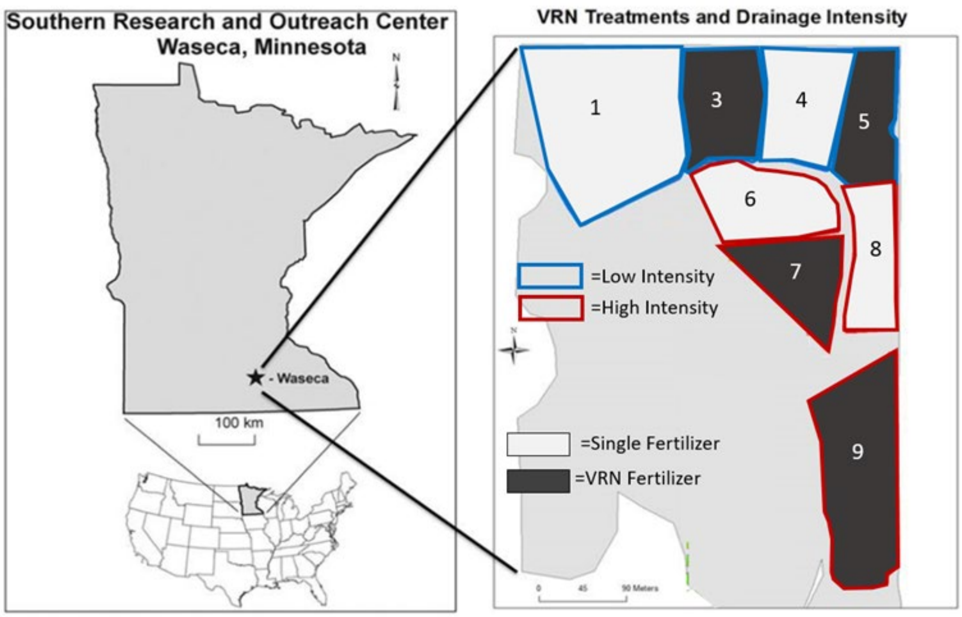

Fig. 4: Study location, drainage intensities and nitrogen treatments.

## Field Management

Corn (*Zea mays* L.) and soybean (*Glycine max* L.) were grown in rotation for four years, starting with soybean in 2003, with corn following corn for the fifth year (a soy-corn-soy-corn-corn rotation). For the period 2003-2008, anhydrous ammonia was applied for corn pre-plant in April at a rate of 142 kg N/ha in 2004, 134 kg N/ha in 2006, and 185 kg N/ha in 2007. No spring nitrogen fertilizer was applied during the soybean years. An application of NPK fertilizer (nitrogen, phosphorus and potassium) was applied following soybean harvest in the fall, at a rate of 66/168/224, 0/0/224, and 27/112/134 kg/ha in 2003, 2005, and 2008 respectively.

In the 2016 growing season, the plots were divided into single pre-plant (PP) and VRN fertilizer treatments. The experimental design was completely randomized with two replicates within each drainage intensity. In 2016, the single pre-plant nitrogen treatment consisted of applying the economically optimum nitrogen rate (EONR of 151 kg/ha based on Minnesota Extension Services recommendations) to maize plots 1, 4, 6 and 8 one day before planting, while the in-season variable rate treatment consisted of a rate of 50 kg/ha of nitrogen applied to Subfields 3, 5, 7 and 9 before planting, and the remaining 46 to 56 kg/ha applied at growth stage V6. In 2017, fertilizer was applied at a slightly higher rate to second year maize plots for the single PP application at a rate of 180 kg N/ha, while the VRN application received a slightly lower amount, with 60 kg N/ha applied at planting, and an additional 80 kg N/ha applied at the V6 stage. Pre-plant fertilizer application occurred on April 30 in 2016, and May 11 in 2017; while the split-application was applied June 20 in both 2016 and 2017. In 2019, N fertilizer was applied at a rate of 222 kg N/ha for the PP plots, while the VRN application received 44 kg N/ha pre-plant followed by an average of an additional 50 kg N/ha at the V8 stage. The VRN side-dress application rate was derived from CropCircle Green NDVI sensing at V6 based on two reference zones, each with nitrogen response plots used for confirming the EONR.

## Drainmod Simulations

### Model Description

The hydrologic model Drainmod-NII was used to simulate drainage, nitrate concentration and loads, and soil nitrogen processes for the drainage plots. Drainmod is a process-based, distributed, field-scale model, developed to describe the hydrology of poorly or artificially drained lands (Skaggs et al. 2012). It conducts water balances on hourly and daily time scales, and predicts hydrologic parameters including infiltration, runoff, evapotranspiration, seepage, water table depth, and subsurface drainage on a daily, monthly, and annual time step. The companion model, Drainmod-NII predicts nitrogen transport and transformation processes in the vadose zone, predicting processes such as mineralization, immobilization, nitrification, as well as nitrogen flows out of the system in the form of plant uptake, denitrification, volatilization, and losses from surface runoff and subsurface drainage (Youssef et al. 2005).

### Initial Model Parameterization

Initial input parameters describing the soil water and chemical properties of the Waseca plots were based on values determined by Luo et al. (2010). Soil samples taken from the site were used to determine model inputs including: soil particle distributions, soil water characteristic curves, and saturated hydraulic conductivity. Hydraulic conductivity showed great variability in both the lab measured samples and county soil survey data (Luo et al., 2010) and was used as a calibration parameter. Soil organic matter (4.7-6.2%) was estimated in each plot using kriging interpolation based on soil sampling data from a 0.4 ha grid taken in the spring of 2016 before planting. Climatic data measured at the Waseca experiment station site for the years 2003-2016 was used as model input, including: daily maximum and minimum temperatures, and hourly precipitation. Simulations were run with a 5-year soybean/corn rotation starting with soybean in 2003 and alternating with corn for 4 years, with the 5$^{th}$ year as corn following corn

### Model Calibration for years 2003-2008

Drainmod was calibrated for the years 2003-2008, corresponding to period of continuous observed drainage and nitrate load measurements. Model calibration was done for one plot within each depth/spacing treatment (plots 3, 4, 6, and 7), and validated for the remaining plots (1, 5, 8, and 9). Ammonium fertilizer was applied only during corn years, 7 days before planting, and incorporated at a depth of 15 cm. For model calibration, fertilizer was applied at a rate of 135 kg N/ha. Model performance was evaluated by calculating the monthly Nash-Sutcliffe Coefficient of Efficiency (NSE) and by visual analysis of monthly trends in the simulated subsurface drainage and nitrate loads compared to the measured data for each plot.

### Model Simulations for 2016, 2017 and 2019

Following calibration, the model was run for a 5 year period (2013-2017) to compare measured data to Drainmod-predicted nitrate concentration and load for plots treated with VRN fertilizer application vs. the single spring pre-plant application. The 5 year simulation utilized a soy-corn-soy-corn-corn rotation. For all plots, fertilizer was applied during the corn years only, and for the first corn year, fertilizer was applied as a single spring application at a rate of 150 kg N/ha, similar to field practices.

Drainmod-NII does not allow for different fertilizer rates within the field, and so fields simulated using the model are treated as homogeneous with regard to soils and management practices. To account for spatial variability in fertilizer application in model simulation, the simulated VRN scenario used the average application rate from the 2016, 2017 and 2019 field work. The average rate took into account the spatially varying fertilizer amounts applied based on proximal sensing of N deficiency. In future, it may be worthwhile to explore how averaging Drainmod results from a range of fertilizer application rates within each plot would affect the water quality predictions. Plots 1, 4, 6, and 8 were simulated using the single PP fertilizer management, with a single application of ammonium N-fertilizer at a rate of 150 kg N/ha, 7 days before planting. Plots 3, 5, 7, and 9 were used to simulate the VRN fertilizer application. The VRN fertilizer management scheme used an application rate of 100 kg N/ha, with half (50 kg N/ha) applied 7 days before planting, with the remaining half (50 kg N/ha) surface applied 60 days after planting.

The model simulated results for nitrate concentration (2016, 2017 and 2019) and load (for 2017 and 2019) were compared against the observed data measured in 2016, 2017 and 2019. The observed concentration data were collected as grab samples, which were assumed to be representative of daily conditions. The daily load values for 2017 and 2019 were calculated assuming the instantaneous flow rates measured were representative of daily conditions. These daily observed values were compared against the average of the simulated data for a seven day period around the measurement date; the average of the predicted value for the day that the observed data was collected and all values predicted within the window of plus and minus three days of that.

### Model Simulation of Improved N Management Practices

Drainmod-NII was then run over a 14 year period (2003-2016) for the 5 year soy-corn-soy-corn-corn rotation using three N treatments for every year corn was grown. The three N treatments including a single pre-plant application in the spring, the VRN application, and a split application scenario which did not take into account the reduced N-rate, but did include changing the timing of application to be the same as the VRN, with an application before planting and one in-season. Plots 1, 4, 6, and 8 were simulated using the single PP fertilizer management, with a single application of ammonium N-fertilizer at a rate of 150 kg N/ha, 7 days before planting. Plots used in the model simulation of the alternative-N practices were based on those that received the VRN fertilizer in the 2016 and 2017 field experiments, and included plots 3, 5, 7, and 9. The VRN fertilizer management scheme used an application rate of 100 kg N/ha, with half (50kg N/ha) applied 7 days before planting, with the remaining half (50 kg N/ha) surface applied 60 days after planting. The split application treatment was modeled using the same plots as the VRN treatment (plots 3, 5, 7, and 9), and same application rate as the single PP (150 kg N/ha), with half of the fertilizer (75 kg N/ha) applied 7 days before planting, with the remaining 75 kg N/ha applied 60 days after planting.

# Results and Discussion

## Results of model calibration

Model performance for the calibration dataset (years 2003-2008), is presented in Table 9 as NSE values based on comparing observed and predicted monthly drainage or nitrate load. Generally, a monthly NSE value of 0.5 or greater is considered acceptable while a value of 0.7 or greater is considered good (Moriasi et al. 2007; Skaggs et al. 2012). Most NSE values are acceptable to good, with the exception being Subfield five. The poor results for Subfield five are likely due to instrument malfunction, resulting in no data collection for the year 2004. While missing data would not affect NSE values, unusually low flow for the year 2008 in Subfield five indicates continuing instrument malfunction that compromised NSE values. NSE values for nitrate loads were higher than NSE values for drainage in three Subfields, nearly equal values for drainage in two Subfields, and lower values in two Subfields. Overall, NSE values for drainage and nitrate load indicate satisfactory model performance.

Table 9: Summary of monthly NSE values for subsurface drainage and nitrate load for Subfields (plots) during calibration and validation (years 2003-2008). Subfields 3, 4, 6, and 7 were used for calibration, while Subfields 1, 5, 8, and 9 were used to validate model performance.

| | Monthly NSE Value | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Plot 1 | Plot 3 | Plot 4 | Plot 5 | Plot 6 | Plot 7 | Plot8 | Plot 9 |
| Drainage | 0.35 | 0.56 | 0.49 | -0.65 | 0.5 | 0.5 | 0.66 | 0.72 |
| Nitrate Load | 0.4 | 0.54 | 0.55 | -1.7 | 0.6 | 0.4 | 0.35 | 0.7 |

## Comparison of Observed and Predicted Nitrate Concentrations for 2016 and 2017

The average of the observed and predicted nitrate concentrations for Subfields treated with single uniform and VRN sidedress fertilizer applications in 2016, 2017 and 2019 are summarized in Fig. 5. For the 2016, 2017 and 2019 growing seasons, the measured concentrations were slightly higher than those simulated by Drainmod. In 2016, the average daily nitrate concentration for the observed and simulated data in the single treatment Subfields equaled 13.2 and 12.4 mg/L, respectively. For the VRN plots, the observed and simulated concentrations were 11.5 and 9.5 mg/L, respectively. In 2017, the nitrate concentration for the observed and simulated data in the single treatment was 11.1 and 10.4 mg/L, while the VRN treatments were 9.1 and 8.5 mg/L respectively. In 2019, observed and simulated nitrate concentrations in the uniform treatment were 11.3 and 112.3 mg/L, respectively. For plots in the VRN treatment during 2019, the observed average daily nitrate concentration was 8.3 mg/L, with model prediction equal to 6.7 mg/L.

In 2016, the simulated VRN Subfields showed on average a much greater percent change in nitrate concentration than the single uniform application Subfields, with a 23% percent reduction predicted by the model, while only a 13% reduction was measured in the field (Fig. 5a). In 2017, the simulated VRN Subfields showed a smaller reduction in nitrate concentration than the observed value, with a 19% reduction predicted by the model, while an 18% reduction was measured in the field (Fig. 5b). In 2019, the simulated VRN Subfields showed a reduction in nitrate concentration of 45%, while the measured VRN Subfields had a 26% reduction.

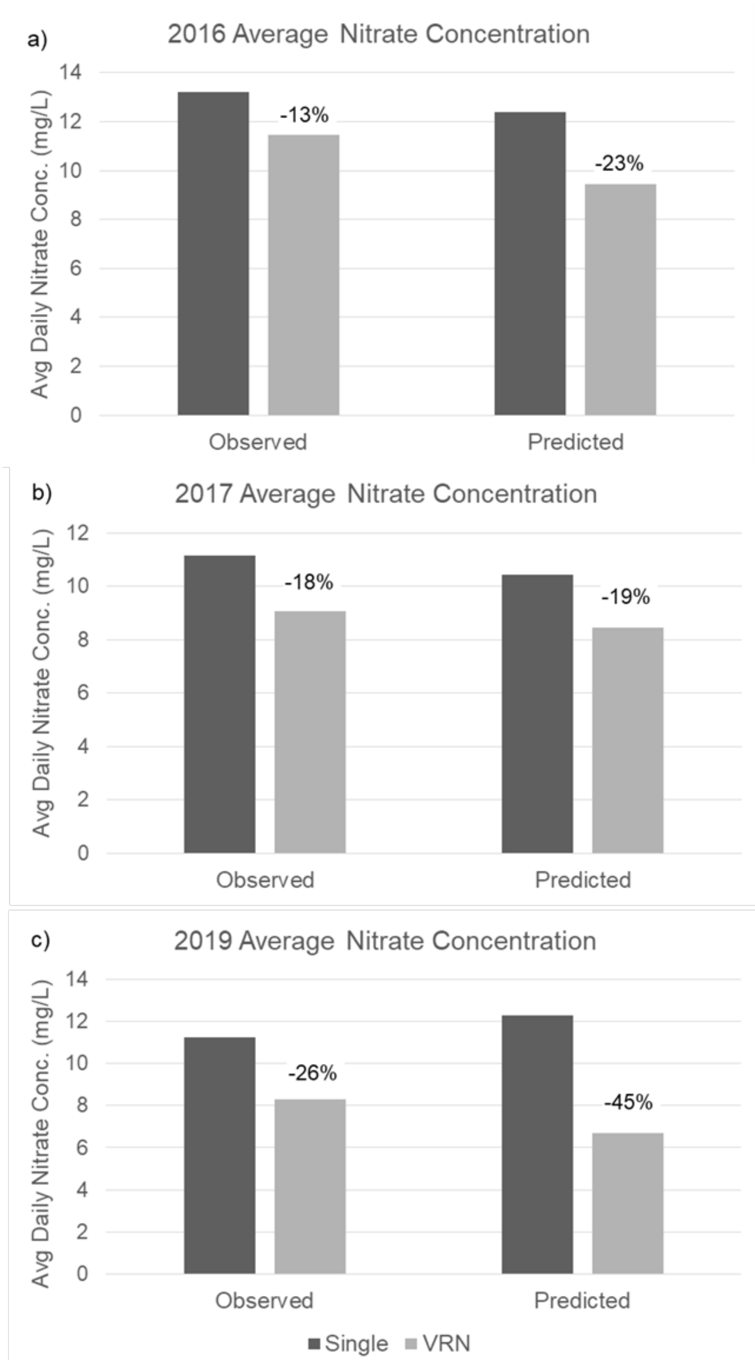


Fig. 5: Observed and simulated nitrate concentration for single uniform pre-plant vs VRN applications in a) 2016, b) 2017 and c) 2019. The observed data are an average of the individual grab samples taken in each Subfield and the predicted data are the 7-day average of model predictions around the measurement date.

Though model and simulated nitrate concentration values are not identical, the model results show reasonable approximation of field measurements. For example, predicted nitrate concentrations are 8.4% smaller than observed concentrations in 2016 for the single uniform fertilizer application. All other comparisons between predicted and observed nitrate concentrations in 2016, 2017 and 2019 show larger differences, with an average reduction of 31.9% from observed values. These differences can be explained based on the sampling methodology for observed data. The observed data were taken as individual grab samples. If stormflow samples had been collected, observed values would likely have been decreased, since nitrate concentrations generally decrease during stormflow. In contrast, predicted data are simulated as the average daily value—which could explain the lower concentration values in the predicted data.

## Comparison of nitrate loads for single, split, and VRN management

Results of DRAINMOD simulation of nitrate load for the years 2013 to 2019 are shown in Fig. 6. The average annual nitrate load shown in the figure is the average of the predicted load for each plot in the single, pre-plant fertilizer treatment (plots 1, 4, 6, and 8), compared to the average of all plots in the VRN treatment (plots 3, 5, 7, and 9). Prior to the year 2016, all plots received the same fertilizer application and timing. Any differences between simulated nitrate loads for the years 2013 to 2015 are due to spatial factors that influence N loads (such as those influencing mineralization and subsurface drainage rates) between the plots. The annual nitrate load was generally related to precipitation, with higher loads and higher load reductions with VRN generally predicted for all strategies during wetter years than dry years.

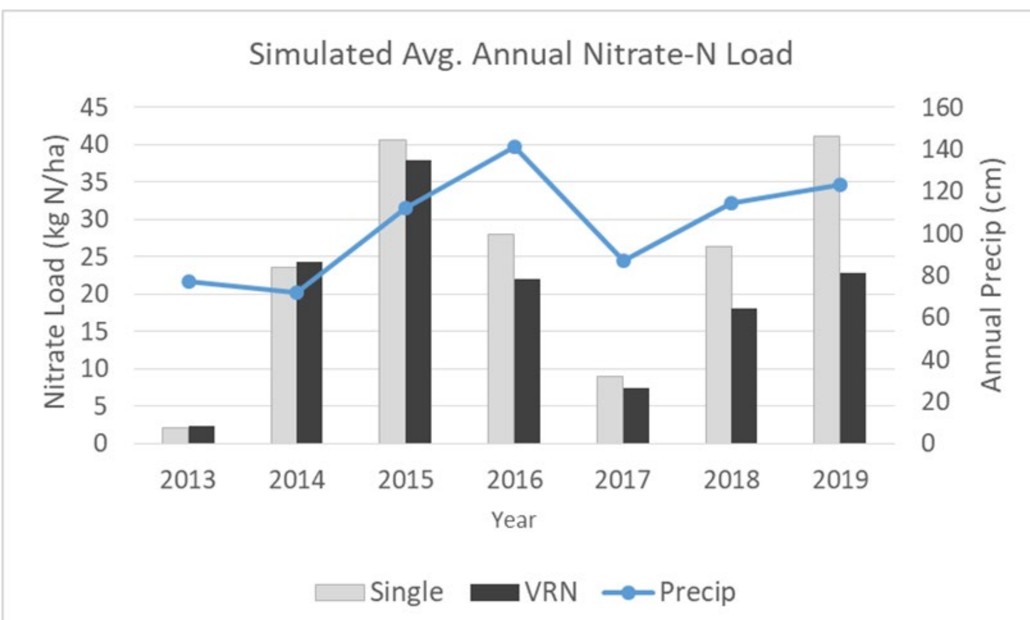


**Figure 6:** Average annual DRAINMOD-simulated nitrate loads for plots at Waseca that were included in the single pre-plant fertilizer treatment, and those in the VRN treatments. VRN fertilizer application treatments began in the year 2016.

Compared to 2014 when all plots received the same fertilizer treatments, once the VRN treatments began in 2016, for corn years (2016, 2017, and 2019), the nitrate loads for the VRN plots show a greater reduction compared to the single pre-plant plots (Fig. 6.). In 2014, the average of the annual N load for plots that would be included in the single pre-plant treatment (plots 1, 4, 6, and 8) was equal to 23.6 kg N/ha. The average of the annual N load for plots that would be included in the VRN treatment (plots 3, 5, 7, and 9) was higher, equal to 24.4 kg N/ha. In comparison, in 2016—the first year of the VRN treatment—the simulated N load for plots in the VRN treatment was lower than the single pre-plant plots, with the load from VRN plots equal to 22.1 kg N/ha compared to 28.0 kg N/ha for the single pre-plant—a 21% reduction in N load. Likewise, 2017 and 2019 also showed reductions in N load. In 2017, the VRN treatment showed a 31% reduction in N loads compared to the single pre-plant treatment (7.4 kg N/ha compared to 8.9 kg N/ha); in 2019 model simulations showed a 44% reduction in the average annual N load for the VRN treatment compared to the single pre-plant (22.8 kg N/ha compared to 41.0 kg N/ha). Plots in the VRN treatment showed reductions in N load during 2018 as well, a year when soybean was grown, and no N fertilizer was applied. The predicted percent reduction in the average annual nitrate load for the years 2016 to 2019 for the VRN treatment compared to the single pre-plant treatment are summarized in Table 10.

Table 10: Percent reduction in the average fertilizer rate, and DRAINMOD-predicted percent reduction in annual N load for plots in the VRN treatment compared to the single pre-plant treatment. The year 2017 was planted in soybean, so no N fertilizer was applied.

| Year | % Reduction in Avg Fertilizer Rate | % Reduction in Avg Annual N Load |
|---|---|---|
| 2016 | 33% | 21% |
| 2017 | -- | 16% |
| 2018 | 22% | 31% |
| 2019 | 52% | 44% |

It is difficult to assess the accuracy of the predicted 28% average reduction in N load for the VRN treatment since there are no other studies in this region that both change the rate and timing of N. Many studies have shown reductions in both N load and concentration for reduced N fertilizer rates (Gast et al., 1978; Kladivko et al., 2004), with Jaynes et al. (2001) finding nitrate loads of 29, 35, and 48 kg N/ha for N rates of 57-67, 114-135, and 172-202 kg N/ha (about a 27% reduction in N load for a 33% reduction in fertilizer). In a modeling study using Adapt-N which compared nitrate load between split application, and split with a reduced rate, Sela et al. (2016) found a 36% decrease in N losses corresponding to a 34% decrease in side-dress N application. This difference in N load for split and split plus the reduced rate is similar to the difference here between Drainmod predicted N-load for the split and VRN treatments, where a 36% reduction in total N application resulted in a 28% reduction in N load.

## Change in N budgets

For all simulation years, Drainmod results show an overall reduction in nitrogen added to, lost from, and stored in the soil system for both alternative N management practices compared the single PP uniform N application (Fig. 7).

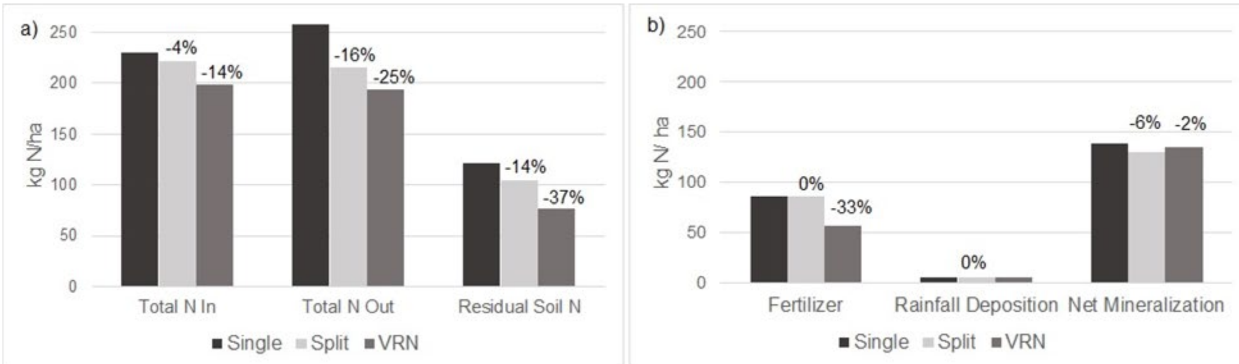


Fig. 7: Simulated nitrogen budgets averaged for Subfields in each treatment (single, split, and VRN) over the 14 year period, including a) total soil nitrogen additions, losses, and residual soil N, and b) sources of nitrogen into the system. In b), the sum of the residual soil nitrogen and total nitrogen out of the system does not equal the total nitrogen into the system. This is because the Drainmod simulations used an initial nitrate concentration in the top of the soil profile of 5 mg/L.

It is not surprising that there is a reduction in nitrogen inputs to the system for the VRN compared to the single application, since the VRN involves applying 33% less fertilizer than the single PP application (Fig. 6b). The split application, however, uses the same amount of fertilizer as the single pre-plant, but still shows an overall reduction of nitrogen inputs. In Drainmod-NII, besides fertilizer application, nitrogen can enter into the system as the result of two processes: 1) rainfall deposition (which was small and independent of N fertilizer treatment), and 2) mineralization of soil organic matter. The reduction in nitrogen into the system for the split application simulated by the model is clearly a result of a reduction in mineralization (Fig. 6b)—an interesting result as it implies that in the model simulation at least, shifting the timing of fertilizer application had an effect on the amount of SOM mineralized.

The average annual residual soil nitrogen decreased for both the split and VRN treatments compared to the single PP, but there was a larger reduction in soil residual N for VRN compared to split. This makes sense for the VRN because there is less fertilizer applied. The overall decrease in nitrogen lost from the system is explained both by the reduction of nitrogen inputs, and also by the reduction in soil storage, which reduced the amount of N available in the soil.

## Conclusions

Nutrient management practices which modify fertilizer application rates and timing to better match plant requirements have been proposed as a way to reduce nitrate nitrogen losses from farm fields and make improvements to surface water quality. In this study, the field-scale hydrologic and nitrogen simulation model Drainmod-NII was used to predict nitrate loads over a 14 year period (2003-2016) for different fertilizer application rates and timing to corn at Waseca in southern Minnesota, USA. The fertilizer practices simulated included a single application in the spring before planting, a split application with half applied pre-plant and half at approximately the V6 stage for corn, and split and variable rate N practice (VRN) which utilized the split timing and a lower rate based on in-season monitoring of plant N requirements. Field trials in 2016, 2017 and 2019 of VRN application at the Waseca AERF site were used to inform the nitrogen rates used for the VRN scenario simulated, and to validate model performance in simulating daily nitrate concentration for Subfields receiving VRN application. Comparison of Drainmod model results for nitrate concentration data measured for the 2016, 2017 and 2019 growing seasons showed good agreement between measured and predicted nitrate concentrations. Alternative nitrogen fertilizer application strategies that change the timing or rate and timing of fertilizer to more closely match plant nitrogen requirements reduced nitrate-N loads from corn and soybean cropping. For a 14 year simulation, model results for split sidedress N application showed a 23% average annual reduction in N load compared to a single pre-plant application, while VRN sidedress application showed a 46% reduction. The larger decrease in the average annual nitrate load for the VRN application, which utilized a reduced fertilizer rate in addition to split sidedress fertilizer application timing, indicates that while changing the timing of fertilizer application reduces N load, changing the rate has an important impact as well. Model simulations showed that changes in nitrogen application timing also reduced the amount of mineralized SOM, and reduced residual soil nitrogen.

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# Chapter 4: Nomographs for Predicting Nitrate-N Loads for Fall, Spring, and VRN Fertilizer Application in Southern Minnesota

## Introduction

Nitrogen management practices which focus on applying the right rate at the right time have been proposed to reduce N loads to surface waters for a number of years (i.e. Nelson, 1985). Split-variable rate nitrogen fertilizer (VRN) application addresses both the temporal and spatial mismatches that occur with single uniform pre-plant applications. In this management, part of the total N amount is applied at or before planting, and part as side-dress during the growing season, delaying full application of fertilizer until corn growth stage V6-V8. Side dressing rates are based on spatial variations in plant N requirements, which can be variable based on crop sensing (Mulla 2013) or in-season modeling of plant available N, reducing over-application of fertilizer on areas with high soil nitrogen content.

Though split-VRN fertilizer application has the potential to reduce nitrate-N loads to surface waters from agricultural fields, there has been little research on how it compares to conventional single, uniform application in this regard. In this study, we used the hydrologic and nitrogen simulation model Drainmod-NII to predict nitrate-N losses for fields managed with a single spring or fall fertilizer application, or split-VRN applications for three sites in southern Minnesota: Waseca, Lamberton, and Willmar. Simulations were done for various nitrogen rate applications and over several years of climate data. The results of these simulations were used to develop regional regression equations that could be used to estimate nitrate-N loss for fall, spring, and VRN application for southern Minnesota.

## Materials and Methods

### Drainmod-NII Model Description

The hydrologic model Drainmod-NII was used to simulate subsurface drainage and nitrate losses at three sites in southern Minnesota: Waseca (described in Chapter 3), Willmar, and Lamberton. Drainmod is a process-based, distributed, field-scale model, developed to describe the hydrology of poorly or artificially drained lands (Skaggs et al., 2012). It conducts water balances on hourly and daily time scales, and predicts hydrologic parameters including infiltration, runoff, evapotranspiration, seepage, water table depth, and subsurface drainage on a daily, monthly, and annual time step. The companion model, Drainmod-NII predicts nitrogen transport and transformation processes in the vadose zone, including processes such as mineralization, immobilization, nitrification, as well as nitrogen flows out of the system in the form of plant uptake, denitrification, volatilization, and losses from surface runoff and subsurface drainage (Youssef et al., 2005).

## Model Calibration

Drainmod-NII was calibrated for measured subsurface drainage flow and nitrate-N loads at each of the three sites. Drainage flow and nitrate losses over multi-year periods had been measured at Waseca, Willmar and Lamberton as part of other research projects. The measured datasets were used to calibrate the model at each site for subsurface drainage and nitrate losses. Initial Drainmod-NII input parameters for simulations of all three sites were based on values reported by Luo et al. (2010), with additional calibration of parameters at each location to ensure good fit between the model-simulated and measured datasets.

Model performance was evaluated by calculating the Nash-Sutcliffe Efficiency (NSE) coefficients and percent bias (PBIAS), which are defined as:

| | | |
|---|---|---|
| | $NSCE = 1 - \frac{\sum_{i=1}^{N}(O_i - P_i)^2}{\sum_{i=1}^{N}(O_i - \bar{O})^2}$ | Eq. 5 |
| | $PBIAS = \frac{\sum_{i=1}^{n}(O_i - P_i)}{\sum_{i=1}^{n} O_i} \times 100$ | Eq. 6 |

Where $O_i$ is the observed (measured) data, $\bar{O}$ is the mean of the observed data, and $P_i$ is the corresponding model-predicted value.

## Site Descriptions

### Waseca

Subsurface drainage and nitrate-N load data measured at the University of Minnesota Southern Research an Outreach Center, in Waseca, MN, were used in Drainmod calibration. The Waseca site consists of nine drainage experimental Subfields ranging in size from 0.8 to 2.4ha. Half of the Subfields have drainage intensities of 13 mm $d^{-1}$ (conventional or "low" intensity), while the other half have a higher drainage rate of 51 mm $d^{-1}$ (high intensity). More detail on the drainage design can be found in Sands et al., (2008). Corn (*Zea mays* L.) and soybean (*Glycine max* L.) were grown in rotation for four years, starting with soybean in 2003, with corn following corn for the fifth year (a soy-corn-soy-corn-corn rotation). The major soil types at the site include Webster silty clay loam (fine-loamy, mixed, superactive, mesic Typic Endoaquolls) and Nicollet clay loam (fine-loamy, mixed, superactive, mesic Aquic Hapludolls).

Average annual precipitation at the Waseca site is approximately 900 mm; precipitation during the growing season (May through September) is approximately 533 mm (averages are the 30 year normal, 1981-2010; NOAA, 2016). Plots were outfitted with tipping buckets to provide a continuous measurement of subsurface drainage flow rates for the years 2003-2008. Nitrogen concentrations were recorded on an event basis for the years 2003 to 2008. Nitrogen load data for the years 2003-2008 were estimated using the Army Corps of Engineers model, FLUX, using the daily flow and sampled nitrogen concentration measurements.

### Willmar

The subsurface drainage and nitrate loads used to calibrate Drainmod for Willmar were obtained from a study by Ghane et al., (2016). This work took place at Goran's Discovery Farm, a privately owned farm located just southeast of the town of Willmar, MN. In their work, daily subsurface flow and nitrate load data were collected for the period 2007-2013 from a 50 ha field with subsurface drainage installed at an average depth of 1.2 m with 24 m spacing. Located in this field was also a surface inlet that connected to the subsurface drainage system. The dominant soil type in the field was poorly drained Canisteo (fine-loamy, mixed, calcareous, mesic Typic Endoaquolls), and Harps loam (fine-loamy, mixed, mesic Typic Calciaquolls). Average annual precipitation is approximately 748 mm; precipitation during the growing season is approximately 510 mm. More detailed information on soil measurements, field measurement of drainage flow and nitrate load, and field management can be found in Ghane et al., (2016).

### Lamberton

Measured drainage and nitrate loads for the years 1990-1998 were obtained from plot studies at the University of Minnesota Southwest Research and Outreach Center (SROC) in Lamberton, MN and used for Drainmod calibration. Plots at this site were planted in a corn-soybean rotation, and had dimensions of 13.7 m by 15.24 m, with subsurface tile drainage placed at a depth of 1.2 m, and spacing of approximately 27 m (personal communication, Jeff Strock, University of MN Extension). Soils at SROC in Lamberton are predominately poorly draining Webster silty clay loam (fine-loamy, mixed, superactive, mesic Typic Endoaquolls), moderately well drained Normania loam (fine-loamy, mixed, superactive, mesic Aquic Hapludolls), and well drained Ves loam (fine-loamy, mixed, superactive, mesic Calcic Hapludolls) (Oquist et al., 2006). Average annual precipitation is approximately 709 mm; precipitation during the growing season (May through September) is approximately 497 mm.

## Model Calibration

### Waseca

Drainmod was calibrated for the years 2003-2008, corresponding to period of continuous observed drainage and nitrate load measurements. Model calibration was done for one Subfield within each depth/spacing treatment (Subfields 3, 4, 6, and 7), and validated for the remaining Subfields (1, 5, 8, and 9). For calibration, ammonium fertilizer was applied only during corn years, 7 days before planting, at a rate of 135 kg N/ha. Climatic data measured at the Waseca experiment station site for the years 2003-2016 was used as model input and for calculating daily potential evapotranspiration (PET) using the Penman-Monteith method. Measured climatic data used as model input included hourly precipitation and daily maximum and minimum temperatures, while daily temperatures, relative humidity, solar radiation, and wind speed were used to calculate PET. Parameters calibrated included: saturated hydraulic conductivity, and soil organic matter.

### Willmar

Drainmod-NII was calibrated for the years 2009-2013. The model was calibrated based on the crop rotation described in Ghane et al,. (2016), which for the years 2009-2013 was corn-soy-corn-corn-corn. For calibration simulations, fertilizer was applied as ammonium at a rate of 160 kg N/ha in the fall prior to planting corn. Hourly precipitation data from the Willmar airport, the nearest weather station, was used as model input. All other climate data—including daily maximum and minimum temperatures, relative humidity, solar radiation, and wind speed—were obtained from the Litchfield airport, located approximately 48 km east of Willmar. Daily PET was calculated using the Penman-Monteith method. Parameters calibrated included: optimum temperature for denitrification, ET factors for the months of April, May, and June, and saturated hydraulic conductivity.

### Lamberton

Drainmod-NII was calibrated for the years 1990-1998, for a corn/soybean rotation, starting with soybean in 1990. Fertilizer was applied during corn years as ammonium at a rate of 150 kg N/ha, a rate typical for the region. Climate input data, including hourly precipitation, daily maximum and minimum temperatures, and daily PET, were obtained from Gary Sands' group at the University of Minnesota. Parameters changed during calibration included: saturated hydraulic conductivity, and ET factors for the months of April, May, and June.

## Drainmod Simulations

Following calibration, Drainmod was run for all three locations for a fall, spring, and split-VRN fertilizer application. For Waseca, simulations were only done for two of the overall nine Subfields (# 4 and 6), representing both high and low intensity drainage (Table 11).

In order to capture the nitrate-loss response with regard to fertilizer application rate, several fertilizer application rates were used in the simulations. For the spring application simulations, nitrogen fertilizer was applied as ammonium in the spring 7 days before planting corn (occurring in late April), at rates of: 10, 100, 150, and 200 kg N/ha. For the split-VRN application, half the total N fertilizer was applied 7 days before planting, and the remaining half applied at approximately the V6 stage for corn, 60 days after planting (mid-June). The application rates used for the split-VRN applications were: 10, 100, 150, and 200 kg N/ha. For the fall application, fertilizer was applied 120 days after soybean was planted (mid-October), at rates of 10, 100, 150, and 200 kg N/ha.

The rate of 150 kg N/ha chosen for these simulations is similar to those used by farmers in the region (Bierman et al., 2011). The application rate of 100 kg N/ha was equal to the fertilizer rate applied to split-VRN fields in a 2016 field experiment at Waseca. The upper and lower amounts (10 and 200 kg N/ha) were arbitrarily chosen to ensure a large range of possible nitrogen fertilizer rates. Simulation rate and timing for each site are summarized in Table 11.

Table 11: Fertilizer rates and timings used for Drainmod-NII simulations. Fertilizer applied in the fall occurred after soybean; in Drainmod, this was set as 120 days after soybean was planted.

| Location | Fertilizer Application Timing | | Total Fertilizer Rate (kg N/ha) | Years Used in Simulation |
|---|---|---|---|---|
| Waseca (Subfields 4 and 6) | Spring | 7 days before planting corn | 10, 100, 150, 200 | |
| | VRN | ½ of total 7 d before planting, ½ of total 60 d after planting corn | 10, 100, 150, 200 | 2003-2016 |
| | Fall | 120 days after planting soybean | 10, 100, 150, 200 | |
| Willmar | Spring | 7 days before planting corn | 10, 100, 150, 200 | |
| | VRN | ½ of total 7 d before planting, ½ of total 60 d after planting corn | 10, 100, 150, 200 | 2008-2013 |
| | Fall | 120 days after planting soybean | 10, 100, 150, 200 | |
| Lamberton | Spring | 7 days before planting corn | 10, 100, 150, 200 | |
| | VRN | ½ of total 7 d before planting, ½ of total 60 d after planting corn | 10, 100, 150, 200 | 1995-2005 |
| | Fall | 120 days after planting soybean | 10, 100, 150, 200 | |

### Regression Analysis

The results of the Drainmod-NII simulations at each of the three study locations were combined in a regression analysis to predict the nitrate loss for spring, fall, and split-VRN fertilizer application. The regression analysis used climate data (including annual and seasonal temperature and precipitation), and fertilizer application rates as potential independent variables.

## Results and Discussion

### Drainmod Calibration

Model performance for predicting subsurface drainage and nitrate losses following validation are shown in Table 12. For drainage flow, model performance is considered satisfactory for a NSE greater than 0.50, or PBIAS between +/- 10 to 15%. For nitrogen loss, satisfactory model performance is for NSE greater than 0.35, and PBIAS between +/- 20 to 30% (Moriasi et al., 2015). Unlike the NSE, PBIAS does not take into account variability in the observed data, and so can bias against datasets that show significant variability.

Table 12: Summary of Drainmod-NII model performance for predicting subsurface drainage and nitrate losses following validation. At Lamberton, Willmar, and Waseca, model performance was evaluated using the annual NSE and PBIAS.

| | Model Goodness-of-Fit for Lamberton, Willmar, and Waseca | | | | | |
|---|---|---|---|---|---|---|
| | Lamberton | | Willmar | | Waseca | |
| | NSE | PBIAS | NSE | PBIAS | NSE | PBIAS |
| Drainage | 0.50 | 13% | 0.39 | -37% | 0.68 | 21% |
| Nitrate Loss | 0.55 | 30% | 0.70 | 38% | 0.78 | 20% |

## Nitrate Losses Predicted by Drainmod-NII

The results of Drainmod prediction for each of the nitrogen rate treatments are shown in Figure 8a, b and c, respectively, for the spring split-VRN application, and fall application. In general, nitrate losses are greatest for fall applications, and least for split-VRN applications, with spring application nitrate losses falling between these two alternative practices. For all application timings, nitrate loss is related to application rate, with greater rates showing greater nitrate losses.

## Regional Regression Equations

The nitrate loss results from the Drainmod-NII simulations for a corn-soybean rotation at Waseca, Willmar, and Lamberton, were best predicted by an exponential equation that used the fertilizer rate applied during corn years and growing season precipitation as the independent (x) variables. Equations best predicting nitrate loss (y) for spring, split-VRN, and fall application timing are shown in equations 7, 8, and 9, respectively:

| | | |
|---|---|---|
| | $y_{spring} = exp(-0.23957 + 0.005361x_1 + 0.034932x_2)$ | Eq. 7 |
| | $y_{VRN} = exp(-0.18481 + 0.004333x_1 + 0.0331071x_2)$ | Eq. 8 |
| | $y_{fall} = exp(-0.05369 + 0.006826x_1 + 0.033587x_2)$ | Eq. 9 |

Where $x_1$ is equal to the rate of nitrogen fertilizer applied (in kg N/ha), and $x_2$ is equal to the precipitation for the months April through September (in cm). The above equations meet standard statistical assumptions.

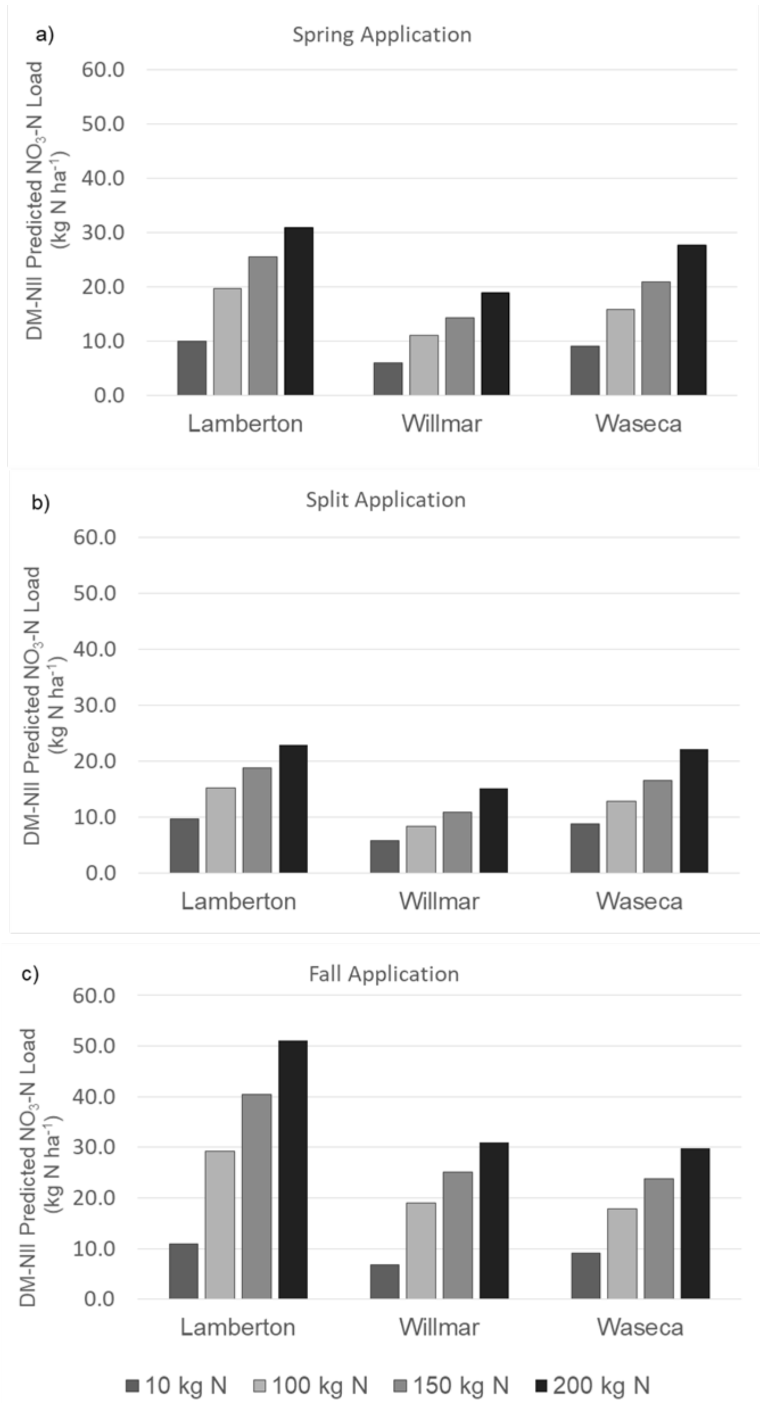


Fig. 8: DRAINMOD-NII simulated nitrate-N load averaged for all years of climate data for each location for: a) spring, b) split, and c) fall fertilizer application.

The spring-application predictive equation had an $R^2$ value equal to 0.56, split-VRN had an $R^2$ value equal to 0.53, and fall $R^2$ value equal to 0.53. The fit of Drainmod and regression predictions are shown in Figure 11.

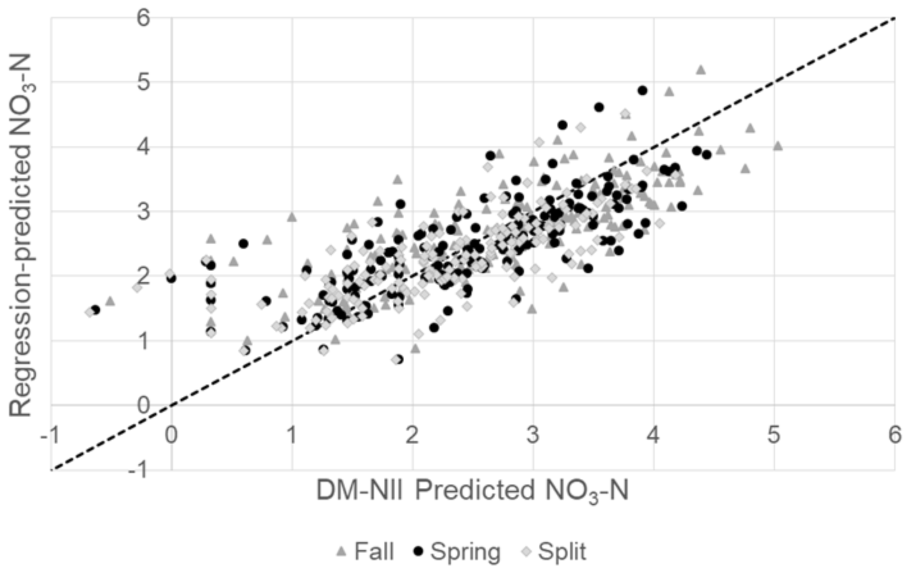


Fig. 11: Ln-ln plots of the results for regression predicted nitrate-N losses at Waseca, Willmar and Lamberton compared to DRAINMOD-NII simulated losses for: spring, split application, and fall application. A natural log (ln) scale was used to achieve the best fit of the residuals. The straight line indicates a 1:1 ratio between DRAINMOD-NII and regression predictions, and a perfect fit between the regression and DRAINMOD-NII results.

## Comparison Between Fall, Spring and Split-VRN Applications

The results of the predictive regression equations applied to a low (120 kg N ha$^{-1}$) and high (180 kg N ha$^{-1}$) fertilizer rate, given a range in precipitation falling during the months of Apr-Sept is shown in Fig. 5. Nitrate-N loads predicted using the regression equations show highest nitrate-N loads for fall application, followed by spring, and then split, with benefits of using spring and split application increases as precipitation increases.

As an example from Fig. 12, at 80 cm of precipitation, and fertilizer applied at a rate of 120 kg N ha$^{-1}$, spring application reduced N load by 22% (6.7 kg N ha$^{-1}$) compared with fall applications; the decrease for split application compared to fall was 37% (11.8 kg N ha$^{-1}$); and the decrease for split compared to spring was 28% (6.7 kg N ha$^{-1}$). At a higher fertilizer rate of 180 kg N ha$^{-1}$ (and 80 cm precipitation), spring application resulted in a 29% (13.6 kg N ha$^{-1}$) reduction, while split application resulted in a 46% (21.9 kg N ha$^{-1}$) reduction relative to fall application, and a 16% (13.6 kg N ha$^{-1}$) reduction compared to spring application. At 80 cm of precipitation, the split application at the higher rate (180 kg N ha$^{-1}$) was still less than a fall application at the lower rate (120 kg N ha$^{-1}$), underscoring the potential benefits of split application, even at higher rates. Though 80 cm of precipitation is higher than the 30-year normal for this region, precipitation at Waseca has been above the 30 year normal for 9 of the most recent 15 years, including a state all-time annual precipitation record of 142 cm (56.24 in) set in 2016, 80% of which fell between the months of Apr-Sept (MCO, 2017). As precipitation increases, the difference between the "best-case" (low fertilizer rate, split-VRN application), and "worst-case" (high fertilizer rate, fall application) scenarios increases.

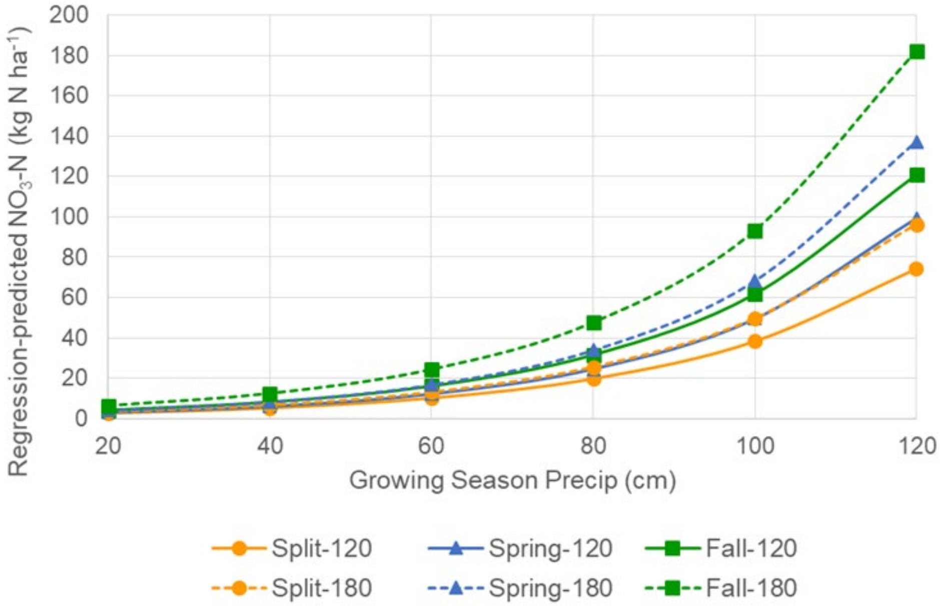


Fig. 12: Regression predicted nitrate loss for southern Minnesota under spring, fall, or split-VRN fertilizer timings. Shown here are the results for a low application rate of 120 kg N/ha (VRN-120, Fall-120, and Spring-120), and a high application rate of 180 kg N/ha (VRN-180, Fall-180, and Spring-180).

## Impacts of Changes in N Fertilizer Management on Water Quality

In southern Minnesota, 60% of growers apply uniform rates of N before planting in the spring, while approximately 32% apply in the fall, and only 8% apply split side-dress N applications (Bierman et al., 2012). Using the results of Eqs. 5-7, weighted to reflect the proportion of area utilizing each of these timing treatments, an estimate of the annual regional loss of N in subsurface drainage systems can be calculated. Weighting Eqs. 5-7, for a fertilizer application rate of 150 kg N $ha^{-1}$ applied 60% in spring, 32% in fall and 8% as a split side-dress application, with precipitation equal to 65 cm (the 15-year average measured at Waseca), the predicted average annual regional loss of N to subsurface drainage systems equaled 25.7 kg N $ha^{-1}$. If producers in the region changed from a majority applying N in the spring and fall, to the majority applying a split N application (going from 60% spring/32% fall/8% split, to 100% split), the regression equation predicts that nitrate loads to surface waters would decrease by 28% to 18.3 kg N $ha^{-1}$.

Nitrogen fertilizer application rates could be further reduced if farmers utilized variable rate technologies that reduced the amount of N fertilizer applied. For a split-VRN application that had a 10% reduction in overall N application applied to the entire region (100% split), nitrate-N loads calculated using the predictive equations show a decrease in N load of 33% to 17.1 kg N $ha^{-1}$ compared to current N losses predicted by the regression equation using the current application rate (150 kg N $ha^{-1}$) and timings (60% spring/32% fall/8% split). For a more robust reduction in N fertilizer of 30%, N losses predicted by the regression equation are 41% less (15.0 kg N $ha^{-1}$) relative to losses predicted given current N application management strategies.

## Conclusions

Nitrate nitrogen (N) from tile-drained agricultural fields is a source of pollution to fresh and marine waters. Sensor-based technologies that allow for in-season monitoring of crop nitrogen requirements may represent a way to reduce nitrate-N losses by allowing for fertilizer application on a more precise spatial and temporal resolution. However, little research has been done to determine its effectiveness in reducing nitrate-N losses. In this study, the field scale hydrologic and nitrogen simulation model Drainmod-NII was used to estimate nitrate-N loads for fertilizer applied to corn given different application rates and application timing approaches for three sites in southern Minnesota: Waseca, Willmar, and Lamberton. The results of these simulation were used in a regression analysis to develop equations to predict nitrate-N loses for the region more generally as a function of fertilizer timing and application rate, as well as growing season precipitation. Fertilizer timing treatments used in model simulation included fall, spring, and variable rate nitrogen (VRN) applications. The VRN application involved half of the total fertilizer rate applied in the spring before planting, with the remaining half applied at approximately corn V6 growth stage. The results of the Drainmod simulations showed the highest nitrate loads occurred for all fall application rates, with VRN having the lowest predicted N losses.

A linear regression analysis of nitrate-N load predicted by DRAINMOD-NII was used to develop equations to predict nitrate-N load for different fertilizer application rates and timings in Southern Minnesota. Exponential regression equations which used fertilizer application rate and growing season precipitation as the independent variables had good agreement with DRAINMOD-NII results with $r^2$ values of 0.56, 0.53, and 0.53 for spring, split, and fall application, respectively. The regression equations were used to predict average N losses given different combinations of precipitation and N fertilizer application rates. Results showed that at 80 cm of precipitation and an application rate of 120 kg N $ha^{-1}$, N loads were reduced by 18% and 39%, respectively, for spring and split application compared to fall. Combining the split timing with lower rates—which could be achieved using VRN technologies—resulted in greater reductions in N losses. Current fertilizer application timing in the region is primarily fall and spring (90% of producers apply uniform N in fall or spring) at a rate of approximately 150 kg N $ha^{-1}$. Based on the results of the predictive equations developed here, changing from the current timing and rate to split-VRN technology could lead to annual regional reductions of 33% given a 10% reduction in N rate, or 41% for a 30% reduction in N rate. These results show that implementation of VRN sidedress applications based on remote sensing of crop N status can result in significant improvements in water quality.

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