



## FINAL REPORT

PROJECT TITLE: Irrigation management impacts on corn yield and nitrate leaching

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## ABSTRACT

Coarse-textured soils in Minnesota have limited water holding capacity which makes irrigation essential to obtain ideal yields for corn, however, excess irrigation has the potential to contaminate ground and surface water sources through deep seepage of applied fertilizers, making irrigation management critical. The objective of this study was to evaluate the impact of different strategies for agricultural irrigation water management on corn grain yield and nitrate leaching losses. In this three-year study (2019-2021), four irrigation scheduling strategies, (i) soil moisture monitoring using soil moisture sensors (SM), (ii) checkbook method of irrigation scheduling (CB), irrigation management assistant tool (IMA) and (iv) EPIC model auto-irrigation (EPIC) were compared under continuous corn cropping system at two sites in Central Minnesota, Becker and Westport sites. Overall, in comparison to the CB method (highest irrigation method), SM, IMA, and EPIC methods recommended 2.58%, 51.05%, and 9.27% less water in irrigation respectively. In terms of grain yield, no significant differences were observed between SM, CB, IMA, and EPIC irrigation treatments in the 2019 and 2020 growing seasons at the Becker site. However, in the drier 2021 season, a grain yield loss of 30%, 27%, and 21% was observed under IMA when compared to SM, CB and EPIC methods, respectively, at the Becker site. At the Westport site, on average, no significant difference in yield was obtained between SM, CB, and EPIC, however, yield under IMA treatment was significantly lower (12%) than CB. The results suggest that nitrate leaching losses can be reduced by altering the rate and frequency of irrigation. Results from this study can aid in the adoption and further development of less labor-intensive and more accurate methods of irrigation scheduling in coarse-textured soils of Minnesota. This study would further help corn growers in Minnesota to decide which irrigation scheduling method would be appropriate for their irrigation management.

## INTRODUCTION

Irrigated agriculture consumes a large portion of freshwater resources accounting for 80% of the nation's consumptive water use. Irrigation is essential for crop production in arid and semiarid regions of the United States, however, in the recent years many humid regions including Minnesota, Wisconsin, Illinois, Missouri, Arkansas, and Louisiana, acreage under irrigation has increased rapidly (USDA NASS, 2018b). In the United States, irrigation is applied to more than two-hundred thousand farms which constitutes 22 million hectares total irrigated farm area (USDA NASS, 2018a). During the past few years, irrigated agriculture has increased significantly in Minnesota. The land under irrigated agriculture in Minnesota has increased by 13% from 2007 to 2012 (USDA NASS, 2017), which continues to increase along with the total volume of water used. More than 25% of groundwater of the state is pumped from irrigation wells, making irrigation the second-biggest groundwater user of the state. Most of these irrigated acres are in the central sands region of the state where agriculture is not economically viable without irrigation. Because of the coarse soil texture, water soaks in quickly and the chemicals applied with water (fertilizers) can also leach quickly into the groundwater, causing not only environmental problems, but also financial losses to the farmer. Many private drinking wells in Central Minnesota have  $\text{NO}_3\text{-N}$  concentrations greater than the USEPA standard for drinking water (10 mg/L) and their reclamation is highly expensive (Minnesota Department of Health, 2021). Twenty-one percent of the total population of Minnesota, which amounts to almost 1.2 million people, uses private wells for drinking water. These problems have led to scrutiny of groundwater by the government, leading to development of new regulatory approaches and groundwater policies (MDA, 2015). Farmers in this region are under increasing pressure from government agencies and environmental groups to reduce their negative impact on groundwater quality. There is a pressing need for research to develop innovative irrigation management strategies to reduce groundwater pumping and nitrate contamination in the central sands region. Moreover, nitrate pollution can lead to eutrophication in surface water bodies (Centers for Disease Control and Prevention, 2015; Goolsby et al., 2001; Mitsch et al., 2001).

Lack of efficient irrigation management is one of the major reasons for negative environmental impacts of irrigated agriculture (J. L. Gabriel et al., 2012; Quemada et al., 2013; Sheikhzeinoddin & Esmaeili, 2017). Various farm management practices are observed to reduce agricultural  $\text{NO}_3\text{-N}$  leaching (Bohman et al., 2020; Everett et al., 2019; José Luis Gabriel et al., 2013; Sigua et al., 2016). In particular, leaching of nitrates below crop root zone can be reduced by managing nutrients and water input to the crop (Chen et al., 2017; Gheysari et al., 2009; Jia et al., 2014). A significant amount of research has been conducted on evaluating the impact of nitrogen fertilizer application rate and timing on nitrate leaching while impact of irrigation scheduling on nitrate leaching is yet to be studied extensively.

Better irrigation scheduling can address the complex challenges we face in the central sands region of Minnesota. Irrigation scheduling enables the irrigator to apply the right amount of water at the right time, which increases irrigation efficiency and reduces nitrate-N leaching. Several types of irrigation scheduling methods have been documented in literature. In general, the irrigation scheduling methods are classified in three broad groups: soil and/or crop monitoring techniques, soil water balance computation using weather data and combination of these techniques. Soil based methods estimates soil moisture in the crop root zone using manual gravimetric method or soil moisture sensors. The manual gravimetric method requires collecting, weighing and drying soil samples which is accurate, but time consuming and expensive. Using soil moisture sensors such as a neutron probe to measure soil water content is also an accurate method, however, has very limited applicability in commercial fields because of special requirements associated with handling of radioactive material (Sui & Vories, 2020). Other soil moisture sensors such as time domain reflectometry (TDR), and capacitance sensors are widely used for irrigation (Evelt and Parkin, 2005; Vellidis et al., 2008; O'Shaughnessy and Sui, 2018). These sensors provide useful information for irrigation scheduling, however, proper installation and maintenance of these sensors is essential for procuring high quality data. Also, these sensors need calibration under specific soil condition. Irrigation scheduling methods based on soil water balance computation using weather data estimate amount of water lost by crop evapotranspiration and amount of rainfall and irrigation entering the crop root zone. One such weather-based methods is the checkbook method that estimates daily soil water depletion in the root zone by tracking daily water inputs (precipitation and irrigation) and water outputs (crop evapotranspiration ( $ET_c$ ) and drainage). It is an excel spreadsheet model that uses temperature-based reference evapotranspiration ( $ET_{ref}$ ) estimated using the simplified Jensen-Haise (1963) equation and crop coefficients that were developed for North Dakota in the 1970's (Stegman et al., 1977). The accuracy of this method can be improved based on regular in-field measurements of soil moisture, without which the method overestimates irrigation by as much as 50% (Jennings and Bohman, 2018). Another weather-based system, the Irrigation Management Assistant (IMA) tool was developed in 2015 for a 7-county area in Minnesota that uses local weather stations to estimate daily reference evapotranspiration and ASCE manual 70 crop coefficients to estimate crop evapotranspiration. It is an easy-to-use web-based tool that does not require daily manual inputs of weather data or other water balance inputs except irrigation. Presently, the tool has been used by growers for irrigating ~2,630 hectares in Minnesota.

Another irrigation scheduling approach is to use a process-based crop simulation model such as the Environmental Policy Integrated Climate (EPIC) model. EPIC is a field scale model and operates on a continuous basis using a daily time step and can perform long-term simulations over several years & has capability to simulate soil water, soil N balance and yield, simultaneously. EPIC model can simulate the variance of soil water and its effects on crop production (Wang et al., 2011). Auto-irrigation option in the EPIC model can be used to estimate the irrigation water requirements at a specific time during the crop growth period. In the past, EPIC model has been successfully used to estimate the irrigation water requirement of corn crop using the auto irrigation trigger at different soil water stress levels (Wriedt et al., 2009).

Based on the technologies and programs used in different studies, there exists a need to compare current technologies of irrigation scheduling of corn via experimentation in different climatic settings and soils. In an irrigation scheduling study, Gu et al. (2017) observed improved crop yield

and water use efficiency with water-stress based irrigation scheduling approach (Gu et al., 2017). Research has confirmed the crop yield and water use efficiency benefits of soil water based, water balance/evapotranspiration-based, and mathematical model simulation-based irrigation scheduling methods over conventional irrigation scheduling methods (Gu et al., 2021; Li et al., 2020; Liang et al., 2016; Migliaccio et al., 2010). Migliaccio et al. (2010) found that soil water based, and ET-based irrigation scheduling methods reduced irrigation water application, while maintaining plant nutrient content, photosynthetic rates and crop yields as compared to set schedule irrigation. Liang et al. (2016) used van Genuchten model and soil moisture sensor data for irrigation scheduling which resulted in about 33% reduction in irrigation water application without impacting crop yield as compared to simplistic yes/no irrigation scheduling tools. Water stress-based irrigation scheduling software developed by Gu et al. (2017) improved water use efficiency by scheduling more frequent irrigations with lower irrigation amounts.

A recent study by Bohman et al. (2020) in Minnesota showed that, a 15% reduction in irrigation rate decreased nitrate leaching by 17%, through reduction in deep percolation. Moreover, prior research also confirms a positive relationship between N and water use efficiencies (Muschietti-Piana et al., 2018; Quemada Miguel, 2016), which makes studying impact of irrigation scheduling on nitrate leaching imperative. Another study conducted by Pang et al. (1998) at Staples, Minnesota using CERES Corn Model simulated that  $\text{NO}_3\text{-N}$  leaching potential was influenced more by irrigation trigger level than by other factors such as N application rates and climate (Pang et al., 1998) due to high permeability and low water holding capacity soils present in the region. Therefore, monitoring water balance and optimizing water input is crucial, especially in soils with low water holding capacities to decrease nitrate leaching (Sigua et al., 2016). In evaluating impact of irrigation management on nitrate leaching, irrigation-induced changes in crop yield also need to be considered, such that reduction in nitrate leaching is achieved without negatively impacting crop yield.

With the availability of different irrigation scheduling methods and different levels of complexity and accuracy associated with each of them, researchers and extension personnel are frequently asked what system to use for irrigation scheduling on a given farm. The goal of this study is to evaluate the available irrigation scheduling methods/tools in Minnesota in order to optimize irrigation scheduling to minimize groundwater nutrient pollution and improve groundwater quality and quantity without significantly impacting corn production. The objective of this study is to evaluate the impact of four irrigation scheduling methods (1) in-field soil moisture monitoring using soil moisture sensors (SM), (2) ET based irrigation management assistant tool (IMA), (3) the University of Minnesota checkbook method (CB), and (4) crop growth model (EPIC), on nitrate leaching and corn grain yield in coarse textured soils.

## OBJECTIVE AND GOAL STATEMENTS

Our main goal is to identify and develop irrigation management strategies that will increase crop water use efficiency, while minimizing nitrate leaching and maximizing crop utilization of soil nitrogen without impacting crop yield. The specific objectives as mentioned above are:

1. Evaluate the impact of 4 irrigation water management strategies on corn yield and nitrate leaching.
2. Calculate the threshold trigger point for irrigation (comparing depletion in available soil water with soil matric potential) using Electric Resistance Sensors (watermark sensors) in coarse-textured soils.

## MATERIALS AND METHODS

Field trials were conducted for three consecutive corn growing seasons 2019, 2020 and 2021 at two research sites in Central Minnesota. One site was located at the Sand Plain Research Farm (SPRF) in Becker, Minnesota (45°23'N 93°53'W) (S1) and the other at the Rosholt Research Farm in Westport, Minnesota (45°42'N 95°10'W) (S2). Both sites have coarse textured soils with low available water holding capacity and need supplemental irrigation to prevent crop water stress. The soil at S1 is Hubbard-Morford complex (sandy, mixed, frigid, Entic Hapludoll) which is a glacial outwash soil and has a sandy alluvium parent material with 0-3 % slopes. The top 120 cm of soil has bulk density of 1.66 g/cm<sup>3</sup>, organic matter content of 0.79 %, volumetric water content at field capacity and permanent wilting point is 0.12 cm<sup>3</sup> cm<sup>-3</sup> and 0.042 cm<sup>3</sup> cm<sup>-3</sup>, respectively (Web Soil Survey NRCS USDA, 2021). The soil at S2 is Arvilla sandy loam (sandy, mixed, frigid, Calcic Hapludoll) with loamy glaciofluvial deposits over sandy and gravelly outwash parent material with 0-2% slopes. The top 4 feet of soil has bulk density of 1.61 g/cm<sup>3</sup>, organic matter content of 0.72 % and 0.13 cm<sup>3</sup> cm<sup>-3</sup> and 0.06 cm<sup>3</sup> cm<sup>-3</sup> field capacity and permanent wilting point, respectively (Web Soil Survey NRCS USDA, 2021). These soils have higher 2.03 % organic matter content percentage at 0-1ft soil depth and 1.23 % at 02ft cm soil depth which is greater than S1. Both the sites have more than 80% sand and less than 4 inch of available water storage in top 4 ft soil profile (Web Soil Survey NRCS USDA, 2021). The climate at both sites is humid/sub-humid with average growing season precipitation (May 1 to Sept. 20) of 224 inch at S1 and 212 inch S2. The average growing season daily maximum temperature was 63 °F and 61 °F at S1 and S2, respectively. Irrigation was applied using a GPS guided variable rate linear move irrigation system (S1- Reinke Manufacturing Co., Inc. and S2- Valmont Industries, Inc., Valley NE) with low energy nozzles. Fertilizer, herbicide and insecticide selection and application rates were based on the University of Minnesota Best Management Practices recommendations. Row spacing was 30 in and the planting density for was 35,500 plants/ac.

### *Experimental layout and irrigation scheduling methods*

The experimental design for this study followed a randomized complete block design with four irrigation scheduling methods replicated 3 times at each site. The four irrigation scheduling methods are the checkbook method (CB) (weather based), online irrigation management assistant tool (IMA) (weather based), soil moisture monitoring using soil moisture sensors (SM) (soil moisture based) and crop growth model (The EPIC crop growth simulation model).

The checkbook method for irrigation scheduling is a weather-based irrigation scheduling method which is fundamentally based on the water balance approach. The change in soil water storage in the root zone of the crop is determined by calculating the difference between total water inflow and total water outflow in the system. The water inflow to the system constitutes precipitation and irrigation amounts and the outflow from the system is crop evapotranspiration and water losses mainly due to runoff and drainage or deep percolation beyond the root zone of the crop.

Broadly, the method operates like a ‘checkbook’ where estimated crop water use for each day is added to the previous day’s soil water deficit and any water inflow due to rainfall or irrigation is subtracted. The soil water deficit or net irrigation requirement is calculated using the following equation.

$$D_c = D_p + ET_c - P - I \quad (1)$$

Where  $D_c$  stands for soil water deficit (net irrigation requirement) in the rooting zone on current day,  $D_p$  is the previous day soil moisture deficit,  $ET_c$  is the crop evapotranspiration on the current day,  $P$  is the precipitation for the current day, and  $I$  is the irrigation amount for the current day.

$$ET_c = ET_{ref} \times K_c \quad (2)$$

Daily crop evapotranspiration ( $ET_c$ ) values are estimated from daily reference evapotranspiration values ( $ET_{ref}$ ) derived from Jensen-Haise equation which involves the incorporation of two weather parameters – solar radiation and temperature and crop coefficient curves ( $K_c$ ) developed for corn for North Dakota (Stegman et al., 1977).

In this study a spreadsheet model of the Checkbook method was used, which required values of daily maximum temperature and daily effective rainfall along with week past emergence of crop to determine Soil Water Deficit (SWD) (Steele et al., 1994; Wright, 2002). Data requirements for effectively using the CB spreadsheet include historical or forecasted maximum daily temperature, AWHC value, crop type, emergence date, rainfall and irrigation data. Also, periodic field visits to monitor crop development and soil water content are recommended (Steele et al., 2010). If a particular growing season produces accelerated or delayed crop development a factious planting date slightly ahead or before the original planting date can be entered in the spreadsheet as an adjustment to account for the change observed in the field (Steele et al., 2010). However, in this

study we did not change the planting date to adjust for the crop development in any season. Management Allowable Depletion (MAD) is the maximum soil water depletion that an irrigation manager allows beyond which irrigation is triggered. MAD was dependent upon crop type and growth stage, and a value ranging from 40-60% of available water holding capacity (AWHC) of soil was chosen in this study.

Irrigation Management Assistant Tool (IMA) is an online platform that automates aspects of daily soil moisture calculations based on a field's soil and current conditions including weather, crop and crop growth stage. This tool was developed in 2016 through a three-year LCCMR project paid by a grant from Minnesota Environmental and Natural Resources Trust fund for the Little Rock Creek Groundwater area and 5-county expanded areas of Hubbard, Becker, Wadena, Otter Tail and Todd counties of Minnesota. In these pilot areas, the tool has been adopted by over 100 regular users to irrigate 5 different crops (corn, soybeans, alfalfa, potatoes, and edible beans) covering roughly 2,630 ha. The success of IMA in these regions and interest shown by other soil water conservation districts in MN and growers throughout MN revealed the need to evaluate the efficacy of this systems in terms of volumes of water applied as compared to other traditional and labor-intensive irrigation scheduling tools. For this project the tool was expanded to Pope and Sherburne Counties of MN to accommodate our research sites. This tool is a weather-based irrigation scheduling tool that uses the water balance approach to estimate soil water deficit (equation 1). Crop evapotranspiration ( $ET_c$ ) was estimated using equation 3.

$$ET_c = ET_r \times K_c \times K_a \quad (3)$$

Where  $ET_r$  is daily alfalfa reference evapotranspiration calculated using Penman-Monteith equation (Monteith 1965; Allen et al., 1998) with a fixed canopy resistance (ASCE-EWRI 2005).  $K_c$  is the crop coefficient and  $K_a$  is the resistance of water transfer to the atmosphere for current percentage of field capacity. Weather variables including solar radiation, rainfall, maximum and minimum air temperatures, wind speed, and humidity were used to compute daily values for  $ET_c$ . For this study, the tool obtained weather data from the weather station at the research site (<http://agweathernetwork.com/>). ASCE-EWRI manual 70 crop coefficient ( $K_c$ ) values for corn were used to model daily  $ET_c$  for irrigation scheduling (Allen et al. 2005). The tool uses the gridded Soil Survey Geographic Database (gSSURGO) for information on site-specific soil physical properties such as soil texture, soil water holding capacity and field capacity. For rainfall data, the IMA tool uses the National Centers for Environmental Prediction (NCEP) stage IV rainfall data. Irrigation is entered by the user. Other user inputs required at the beginning of the irrigation season include field location, field irrigation delivery rate (gallons per minute), crop type, initial soil moisture, planting date and maturity date. The soil water balance estimated using equation 3 can be overridden by the user but in our study, we did not override the soil water balance values and used the tool estimated values for irrigation scheduling. Similar to MAD value used in the CB method the IMA tool uses a minimum allowable soil moisture (MASM) value which represents irrigation trigger. The MASM value is based upon crop, crop growth stage, planting date and soil

properties at the field. The MASM values keep on changing automatically with the progression of the crop and the growing season. The IMA tool monitors field water balance (FWB) throughout the growing season and irrigation is triggered when FWB reaches MASM.

Soil-moisture based irrigation scheduling involves direct calculation of soil water deficit through field measurements of soil water content. In this study neutron moisture meter, InstroTek 503 ELITE Hydroprobe, was used to conduct weekly measurements of volumetric water content of soil. Further, volumetric water content was used to calculate soil water deficit in the root-zone of the crop. Irrigation was triggered whenever the soil water depletion in the root zone was 40%-60% (depending on corn growth stage) of AWHC of soil. As in the case of previous scheduling methods, irrigation amounts were kept in accordance with soil water deficit experienced by soil, to bring back the soil water level close to field capacity while leaving some room for expected precipitation events.

Environmental Policy Integrated Climate (EPIC) Model is a mathematical model that simulates crop growth parameters (Texas A&M, 2021). It is a field scale model that particularly simulates yield, water and N balance. It functions at a daily time step. In this model various attributes including weather data such as solar radiation, maximum and minimum daily temperature, precipitation, relative humidity, windspeed and soil properties such as soil water upper limit, soil water lower limit, soil texture and crop attributes such as crop type, planting date and cropping system are taken as inputs. The irrigation application method in the EPIC model was specified by irrigation code, i.e. [1] for sprinkler irrigation. In this study, for one of the sites (S2) EPIC model was previously calibrated using 4 years of field data (2011-2014) from an adjacent site from another study. Pre-calibrated EPIC model was used for the year 2019, while fine-tune calibration was performed using these two sites data, to validate the model for years 2020-21. Field measurements were utilized for calibration and validation of the simulated outputs. EPIC model auto-irrigation is based on the upper 20 cm soil profile moisture contents. Model was aimed to apply minimum irrigation water to minimize the deep percolation losses without impacting the yield. Soil matric potential values for each site were adjusted such that any significant decrease in yield was not modeled. Minimum irrigation interval was adjusted to 3 days. Maximum and minimum values of irrigation was adjusted to 10 and 25.4 mm, respectively. Matric potential values selected for auto-irrigation at Becker and Westport sites were 300 and 450 kPa, respectively.

### Nitrogen fertilizer application

In this study, a uniform amount of N fertilizer 240 lb./acre (Urea and ESN) was applied across all treatments for all site years. The University of Minnesota BMPs recommend split applications of N fertilizer for irrigated sandy soils during the corn growing season (Lamb et al., 2015). At S1, a split application of N fertilizer rate 80, 80 and 80 lb./acre was conducted at planting, V2 and V8 corn growth stages. At S2, a split application of N fertilizer rate 120 and 120 lb./acre was conducted

at V2 and V8 corn growth stages. Fertilizer application was followed by an irrigation or rain event to incorporate fertilizer N into the soil.

### Volumetric water content measurements

Volumetric water content (VWC) was measured in all study plots at both sites throughout the growing season on a weekly basis using a neutron moisture meter (InstroTek 503 ELITE Hydroprobe). At the beginning of the growing season, metal access tubes were installed in the center row of each plot up to 4 feet soil depth at S1 and up to 3 feet depth at S2, due to presence of gravel below 3 feet depth at S2. The access tubes were covered with a cap to prevent any water from precipitation or irrigation events from going into the tubes. The VWC was measured at intervals of 12 inch depth at S1 and at intervals of 6 inch depth at S2. Soil water deficit was calculated based on the VWC readings and irrigation was scheduled based on these measurements in SM treatment. Soil water measurements were also used in estimating water balance crop evapotranspiration from each treatment.

### Soil water balance

Crop evapotranspiration for all irrigation treatments was estimated using the water balance approach. In a soil-water-plant system change in soil water storage must be equal to the difference between total water inflow to the system and total water outflow from the system. Precipitation (P) and irrigation (I) were considered as inputs to the system as they add water to the system and crop evapotranspiration (ET<sub>c</sub>), runoff (R) and drainage (D) were taken as negative as they take water from the system.

$$dS = P + I - ET_c - R - D \quad (4)$$

Where, dS = change in soil water storage (mm); P = Precipitation (mm); I = Irrigation applied (mm); R = Runoff (mm); D = Drainage (mm)

The change in soil water storage (dS) was calculated from weekly soil water content measurements by the neutron probe. Precipitation amounts were obtained on a daily basis from local weather station data at research sites. Irrigation amounts recommended by different irrigation scheduling methods were used. Runoff was calculated according to the USDA NRCS curve number method for estimating surface runoff (USDA, NRCS, 1985). Drainage values simulated by the EPIC crop growth model were incorporated in this equation. From equation (3), crop evapotranspiration was computed according to the following equation -

$$ET_c = P + I \pm dS - R - D \quad (5)$$

Total water application (TWA) in this study is the total amount of water input to the cropping system during the corn growing season, combining precipitation and supplemental irrigation. Seasonal Crop Evapotranspiration (ET<sub>c</sub>) is the portion of the total water application which is

utilized by the crop throughout the growing season. In this study, Percentage Water Use (PWU) is the percentage of total water applied used as crop evapotranspiration.

$$PWU = \{(ET_c / TWA) * 100\} \quad (6)$$

Where, TWA - Total water application (mm);  $ET_c$  - Crop Evapotranspiration (mm); PWU - Percentage Water use (mm)

### Soil water nitrate concentrations and load

For the measurement of soil water  $NO_3$  concentration, suction cup lysimeters with porous ceramic cup (100 KPa high flow, Soil Moisture Equipment, Santa Barbara, CA) were installed at depth of 4 feet approximately 1 week after planting. For installation, a soil auger was used to bore a hole of slightly larger diameter than that of the lysimeter and silica flour slurry was poured at the bottom of the hole to ensure proper hydraulic contact with the soil. Bentonite was added alongside the periphery of the pipe to avoid any preferential flow of water from surface to the suction cup along the periphery of the pipe and soil was carefully poured back and packed around the tube after putting the lysimeter in the borehole. Two suction cup lysimeters in 2019 and 2020 and one in 2021 were installed in the center row of each plot such that they are equidistant from the center of the row, such that representative water samples from both sides of the plot can be obtained. Sampling was done manually by using a hand pump at a suction of 30 KPa to collect soil water draining through the soil at the depth of installation. Samples were collected approximately once a week and samples were kept frozen until analyzed. Drainage values simulated from EPIC crop growth model, were multiplied with nitrate concentration data to calculate the total  $NO_3$ -N leaching losses for all treatments.

### Crop yield, dry matter content and N uptake

Plant and grain samples were collected from each plot at both sites for all growing seasons in order to measure crop biomass and N uptake. Corn grain yield was obtained and adjusted to  $155 \text{ g Kg}^{-1}$  of grain moisture content. Plant samples were collected from each plot at V8, R1 development stages and physiological maturity (R6). A total of six representative plant samples were randomly taken from each plot: three consecutive plants from 2 rows. Whole plant samples were manually cut with knives, passed through a chipper and put in labeled bags. The samples were then dried at  $60^\circ\text{C}$  and weighed before being ground by a Thomas Wiley mill. The samples were then sent to laboratory for Total-N analysis, where samples were weighed and combusted in an Elementor varioMAX cube to determine Total-N. At harvest, in late October, grain samples were collected from center 4 rows of each plot with 1.5 m end-trimming on either side of the plot with the combine harvester. The grain was oven dried, ground and sent to laboratory for combustion analysis, for Total-N in grain obtained through the same procedure as above. Post-harvest soil samples were also taken from each plot at soil depths - 0.3 and 0.6 m in order to determine remaining nitrate-N concentration in soil. The samples were collected with the help of a tractor mounted Giddings

probe at two depths from the center row of each plot. The soil samples were also ground and sent to laboratory where Lachat QuickChem 8500 Flow Injection Analyzer was used for Nitrate-N analysis.

### Statistical analysis

Data was analyzed with RStudio Version 1.2.1335 (2009-2019 RStudio, Inc.). Analysis of Variance and mixed effect models were used to identify significant differences in parameters of interest – yield, nitrate leaching, crop evapotranspiration and nitrate leaching at  $\alpha = 0.05$  across treatments. Irrigation scheduling methods or irrigation treatments were considered as fixed effects while block and year were considered as random effects. Additionally, impact of precipitation was observed on above mentioned crop parameters with year as fixed effect.

## RESULTS AND DISCUSSION

Weather data were obtained from the Minnesota Department of Agriculture weather station located at the research sites as a part of Minnesota Agriculture Weather Network. At both sites, greater atmospheric demands were observed in 2021 as compared to 2019 and 2020. In addition, 2021 had 26 and 13 fewer precipitation events than 2019 and 2020 at S1 and 15 and 17 fewer events than 2019 and 2020 at S2, respectively, which resulted in 13 inches and 4 inches lower growing season precipitation in 2021 as compared to 2019 and 2020, respectively at S1. Though the seasonal total precipitation in 2021 at S2 was only 1.2 inch lower than 2019 and 2 inch greater than 2020 growing season due to very heavy precipitation at the end of the season in August, September and October, during the peak growing season (June and July), the precipitation was 3 and 5 in lower than 2019 and 2020, respectively. All site years except 2019 growing season at S1 and S2 experienced below-normal precipitation amounts during the growing season as compared with the 30-yr normal of 22 in and 20.5 in at S1 and S2, respectively (Source of 30-yr normal: National Oceanic and Atmospheric Administration). Moreover, for the months of June and July which are peak water use months for maize (Table 1), 2021 had significantly ( $p < 0.05$ ) lower precipitation as compared to the normal. Hence the average irrigation requirements for 2020 and 2021 were higher than that of 2019 among all irrigation methods at both sites. In 2021 although some high precipitation events at S1 and S2 increased total precipitation for mid to late-season months, their contribution towards meeting crop water requirements was limited by excessive water loss to drainage. For both sites, the average monthly temperature in 2019 growing season mostly remained below the 30-yr normal mean temperature. For 2020 growing season, the average monthly temperature was higher than the normal for the months of June, July and August at both sites and also greater than in 2019. The 2021 growing season experienced greater than normal temperatures throughout the growing season and was a drought year on record in Minnesota. In 2019, both lower temperatures and higher precipitation reduced irrigation requirements of maize since most of the maize water needs were

fulfilled by precipitation. In addition to average temperature and seasonal precipitation, plant water use, and surface evaporation are influenced by other climatic variables, including daily wind speed, and solar radiation. For most of the season wind speed was not different between years, however, greater wind velocities were observed in 2020 for the month of June at S2 as compared to other two years. Also, in 2021, greater wind speed existed in the month of August at both sites as compared to 2019 and 2020 growing seasons. On average, greater solar radiation was observed in 2021 for both sites and lowest solar radiation was observed in 2019.

Table 1. Monthly and growing season total precipitation (in) for years 2019, 2020, 2021 and 30-yr normal at the Sand Plain Research Farm, Becker, MN (S1) and Rosholt Farm, Westport, MN (S2)

Month	S1				S2			
	30-yr	2019	2020	2021	30-yr	2019	2020	2021
May	4.8	6.2	1.6	1.6	3.0	6.0	0.8	0.7
Jun	4.8	3.3	3.9	0.7	4.3	2.6	2.8	1.2
Jul	4.1	4.1	3.7	1.2	4.1	4.2	6.5	2.8
Aug	2.8	3.4	4.6	4.2	3.7	3.1	5.8	7.0
Sep	3.1	4.2	1.0	3.5	2.9	8.3	0.9	3.8
Oct	2.9	4.0	1.4	1.6	2.5	2.9	1.7	4.6
Growing season total	22.4	24.9	15.8	11.9	20.6	21.2	18.0	20.1

Source of 30-yr normal (1991-2020): National Oceanic and Atmospheric Administration.  
Yearly data collected at research sites.

Table 2. Monthly and growing season daily mean temperature (°F) for years 2019, 2020, 2021 and 30-yr normal at the Sand Plain Research Farm, Becker, MN (S1) and Rosholt Farm, Westport, MN (S2)

Month	S1				S2			
	30-yr	2019	2020	2021	30-yr	2019	2020	2021
May	57.9	53.4	56.4	56.9	57.0	51.7	54.6	55.5
Jun	68.5	67.0	70.8	73.4	66.3	65.9	69.6	70.7
Jul	71.5	71.9	73.6	72.5	70.4	70.1	71.6	71.0
Aug	68.8	67.5	69.7	71.4	68.3	64.9	68.1	68.6
Sep	61.7	62.9	58.1	63.0	60.3	60.9	56.2	61.5
Oct	48.3	43.5	41.3	52.3	46.5	41.3	38.7	50.8

Growing season average	62.8	63.2	63.9	66.2	61.5	61.0	61.1	62.7
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Source of 30-yr normal (1991-2020): National Oceanic and Atmospheric Administration.  
Yearly data collected at research sites.

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### Treatment effect on irrigation amounts and timing

The irrigation scheduling methods used in this study had a significant ( $p < 0.05$ ) impact on the amount and timing of the irrigation (Fig. 1). In total there were 8, 9, and 15 irrigation events in 2019, 2020 and 2021, respectively, for SM plots at site S1. For the same years and site, CB plots received 7, 5 and 12 irrigations, EPIC plots received 8, 8 and 17 irrigations and IMA plots received 2, 5, and 10 irrigations, respectively. At S2, in 2019, 2020 and 2021, SM plots received 1, 6, and 9 irrigations, CB plots received 3, 7 and 8 irrigations, EPIC plots received 5, 6 and 15 irrigations and IMA plots received 0, 2, and 5 irrigations, respectively. In all years, S1 received significantly higher irrigation than S2 because of differences in the climatic conditions and soil types between the two sites. Typically, site S1 had higher temperatures and higher evaporative demand resulting in higher irrigation. As precipitation is the main soil water input, thus high variations in precipitation input and pattern caused high variation in irrigation water demand. Year 2021 was very dry and thus showed substantially high irrigation water input. In all years and sites, lowest irrigation was recommended by the IMA tool which was significantly lower than other treatments. The highest irrigation was recommended by SM method at site S1 in all years whereas at site S2, highest irrigation was recommended by CB method in 2019 and 2020 and by EPIC method in 2021. There was no significant difference in total seasonal irrigation amounts between SM, CB and EPIC. Overall, in comparison to SM method, IMA and EPIC methods recommended 56% and 9% less water in irrigation whereas CB method recommended 8% more water in irrigation. Significantly lower irrigation in IMA treatment particularly in 2019 could be due to the overestimation of precipitation in the IMA tool. The IMA tool uses the National Centers for Environmental Prediction (NCEP) stage IV data for precipitation estimation for a particular location (Du, 2015). The NCEP stage IV rainfall data is based on the multi-sensor 6-hourly analyses on local 4km polar-stereographic grids and uses a mosaicking technique that combines data from 12 River Forecast Centers (RFCs) in CONUS. Studies have shown that the quality control at the hourly scale implemented at the RFCs is automated, and often this process cannot identify bad rain-gauge reports therefore some caution should be used when using radar derived precipitation data (Nelson et al. 2016). In our study, the precipitation estimation by the IMA tool was 8%, 3% and 10 % greater than the measured precipitation on-site at S1 and 25%, 6% and 1% greater at S2. The higher precipitation estimation by the IMA tool skewed the water balance in the IMA tool resulted in lower irrigation recommendations. In addition, we observed that the IMA

tool tends to overestimate the water holding capacity of the soil which resulted in higher recommended depletion values resulting in lower irrigations (Fig. 1).

Seasonal trends of cumulative irrigation water (Fig. 1) indicated that in 2019 and 2020 which were comparatively wetter years than 2021, the irrigation treatments had a similar trend for the respective sites. For S1, highest irrigation was recommended by SM followed by CB, then EPIC and lowest in IMA. Similarly, at S2, lowest irrigation was observed under IMA tool whereas highest was under CB followed by EPIC and SM. For the drier 2021 year, for most part of the season, both sites had the similar trend. The highest irrigation was recommended by EPIC followed by SM and CB and the lowest irrigation in IMA tool at S2. In general, the primary difference between EPIC, and SM and CB treatments was that EPIC generally recommended smaller depths of irrigation water per irrigation whereas CB and SM treatments recommended higher depths per irrigation. The SM and CB treatments had similar trend in amount of cumulative irrigation water in all years except in 2019 at S2, though timing of irrigation events was different. The CB method spreadsheet includes tables with estimated crop water use values for maximum temperature ranges at different growth stages for corn grown in MN. Depending on the growth stage of the actual crop in the field, the crop water use estimates in the spreadsheet could be changed to match the actual growth stage in the field. However, in this study, we used the default tables based on maximum temperature values without changing the crop water use estimates based on the actual growth stage of the crop that might have generated a cumulative error over time because of which the timing of irrigation was slightly different than SM method.

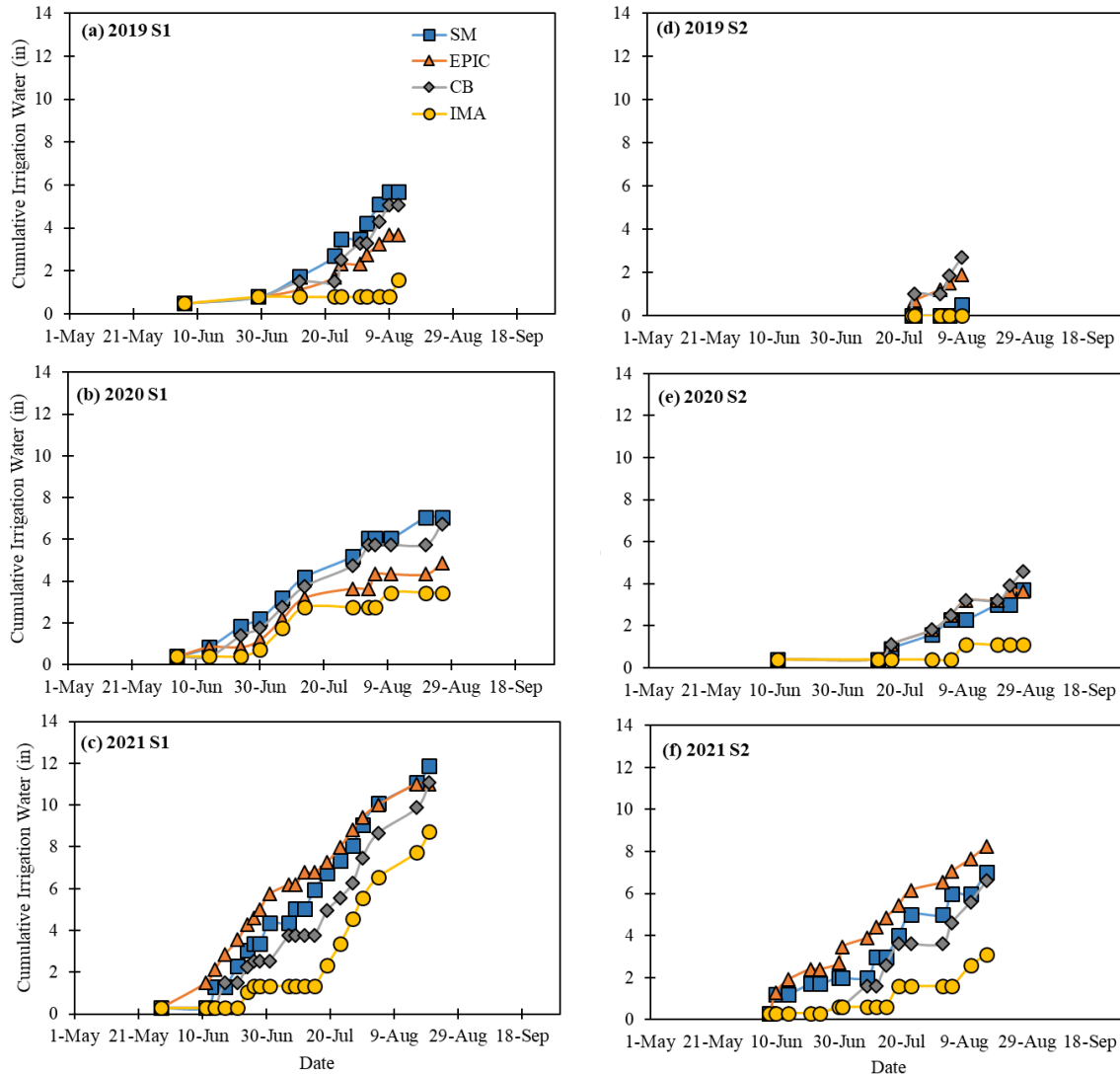


Figure 1. Cumulative irrigation water depth applied with time for SM, CB, IMA and EPIC treatments for 2019, 2020 and 2021 at Sand Plain Research Farm, Becker, MN (S1) and Rosholt Farm, Westport, MN (S2)

### Treatment effect on seasonal crop evapotranspiration ( $ET_c$ )

Maize seasonal  $ET_c$ , total water application (TWA = irrigation + precipitation), and percent water use (PWU =  $(ET_c / TWA) * 100$ ) for each treatment and site-year are summarized in table 3. The maize  $ET_c$  increased linearly with increasing irrigation and varied from 18 in to 22.6 in at site S1 and 14 in to 19 in at site S2. In all growing seasons, the highest estimated  $ET_c$  was observed under SM treatment (21 in) at site S1, whereas at site S2, the highest  $ET_c$  was observed under EPIC treatment (17.6 in). At S1, highest  $ET_c$  corresponds to highest irrigated treatment (SM) whereas at S2, two out of three years, the highest irrigation was applied in CB treatment which did not have the highest  $ET_c$  indicating more water losses under CB treatment. The main difference between

CB treatment which was the highest irrigation treatment and EPIC treatment which was the highest ET<sub>c</sub> treatment, was the difference in irrigation frequency and amount of water applied per irrigation. Specifically in 2021, which was the drier year, in the peak ET<sub>c</sub> months, smaller irrigation depths per irrigation event were recommended by the EPIC treatment resulting in more frequent irrigations, and higher crop water use. It has been previously observed that smaller amounts of more frequent irrigations decrease deep percolation losses, leading to higher availability for plant use (Steele et al., 1994). While Irmak et al. (2016) who found no change or decrease in ET<sub>c</sub> when moving from low to high irrigation frequency treatment, however the irrigation system used in that study was subsurface drip irrigation which has minimal evaporation losses thus smaller changes in ET<sub>c</sub>. Overall, our results indicate that ET<sub>c</sub> is not only a function of climatic variables and total irrigation amount but also timing and frequency of irrigation, precipitation, and soil characteristics (Irmak, 2015). Overall, there is no significant (p<0.05) difference in ET<sub>c</sub> between SM, CB and EPIC, however, the IMA treatment ET<sub>c</sub> was significantly lower than other treatments.

Table 3. Seasonal crop evapotranspiration (ET<sub>c</sub>), total water application (TWA), and percent water use (PWU) for four irrigation scheduling methods (SM, CB, IMA, EPIC) for 2019, 2020, and 2021 growing seasons at Sand Plain Research Farm, Becker, MN (S1) and Rosholt Farm, Westport, MN (S2).

Year	Irrigation Treatment	S1			S2		
		ET <sub>c</sub> (in)	TWA (in)	PWU (%)	ET <sub>c</sub> (in)	TWA (in)	PWU (%)
2019	SM	22.6 ± 0.3 a	30.6	73.9	14.6 ± 0.3 b	21.7	67
	CB	22 ± 0.3 a	30.0	73.5	15.5 ± 0.2 a	23.9	64.7
	IMA	20.1 ± 0.6 b	26.5	75.7	14.3 ± 0.2 b	21.2	67.2
	EPIC	22 ± 0.6 a	28.6	76.9	15.7 ± 0.1 a	23.1	67.9
2020	SM	19.6 ± 0.4 a	22.9	85.7	17.6 ± 0.7 a	21.7	80.9
	CB	19.5 ± 0.3 a	22.6	86.4	17.5 ± 0.4 a	22.6	77.4
	IMA	18.1 ± 0.5 b	19.3	94.1	16.4 ± 0.8 b	19.1	85.9
	EPIC	19.2 ± 0.5 a	20.7	92.8	17.9 ± 0.3 a	21.7	82.6
2021	SM	21 ± 1 a	23.8	88.3	18 ± 0.3 b	25.8	70

	CB	20.7 ± 0.4 a	23	90.2	16.9 ± 0.6 c	25.4	66.5
	IMA	19.3 ± 0.3 b	20.7	93.5	14 ± 0.5 d	21.9	63.9
	EPIC	21 ± 0.2 a	22.9	91.5	19.3 ± 0.3 a	27	71.3
	SM	21.1 ± 1.2 a	25.8	81.8	16.7 ± 1.5 a	23.1	72.5
Mean	CB	20.8 ± 1 a	25.2	82.5	16.6 ± 0.8 a	24	69.3
	IMA	19.2 ± 0.8 b	22.2	86.6	14.9 ± 1.1 b	20.7	71.8
	EPIC	20.7 ± 1.1 a	24.1	86.1	17.6 ± 1.5 a	23.9	73.6

The relationship between seasonal irrigation and maize  $ET_c$  is presented for each site year in fig. 2. In general, the  $ET_c$  increased with increase in irrigation for all site-years and pooled data. At site S1, the extremely wet 2019 growing season had a different relationship between  $ET_c$  and irrigation amount due to which the data points of this site-year are shown separately. Similar results were obtained in the study conducted by Irmak (2016) in Nebraska where the extremely wet year of the 2008 growing season showed a different relationship between  $ET_c$  and irrigation than the rest of the years. For our study, a 1 inch increase in irrigation amount resulted in a 0.6 in, 0.31 in and 0.51 in increase in  $ET_c$  in 2019 at site S1, for the pooled data at S1 and for the pooled data at site S2, respectively. These numbers are lower than what Irmak (2016) and Sharma and Irmak (2021) have found at Nebraska, indicating that crop  $ET_c$  is less sensitive to irrigation increase in the Upper Midwest than southern parts (Steele et al., 1994) (Sharma & Irmak, 2021). Comparing the two sites, the relationship between the two variables was much stronger at site S1 ( $R^2 = 0.89$ ) than site S2 ( $R^2 = 0.62$ ). These differences could be attributed to average wet conditions at S2 than S1 (three-year average precipitation at S2 was greater than three-year average precipitation at S1). Similar results were obtained by Irmak (2016) where wet years had weaker relationships than the pooled data. However, in our study no significant difference in  $R^2$  was observed between 2019 and pooled data at site S1.

For years 2020 and 2019 at both sites, greater PWU was obtained under IMA or EPIC and lower PWU was obtained under either SM or CB method. In 2021, the ranking order was the same as

2019 and 2020 at S1, whereas at S2, IMA treatment had the lowest PWU. This could be due to a significant decrease in  $ET_c$  under IMA (15 in) in 2021 as compared to other years. On three years average basis, CB treatment had the lowest PWU consistently. Studies show that as PWU increases, less water is lost to deep percolation during the season, thereby reducing the potential for nutrient leaching (Steele et al., 1994). On this basis, we expect greater potential of nitrate leaching to groundwater under CB or SM method whereas lowest leaching under IMA and EPIC. The measured nitrate leaching results from the present study are presented in the later section of this manuscript.

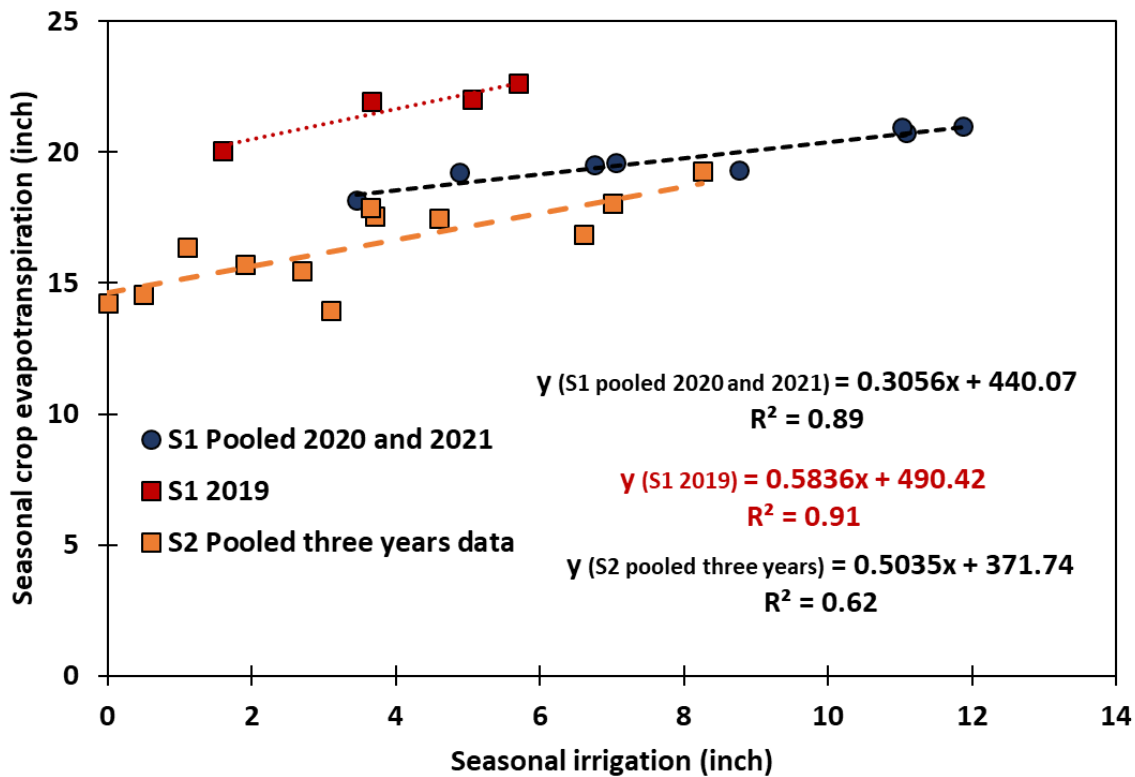


Figure 2. Relationship between seasonal irrigation amount and seasonal maize crop evapotranspiration ( $ET_c$ ) for combined years of 2020 and 2021 for Sand Plain Research Farm, Becker, MN (S1), individual year of 2019 at Sand Plain Research Farm, Becker, MN (S1), and combined years of 2019, 2020 and 2021 for Rosholt Farm, Westport, MN (S2).

#### Treatment effect on maize N uptake

Crop N uptake at V8, R1 and R6 maize growth stages for all site years of the study are presented in Table 4. In general, significant differences were not observed in N uptake between irrigation treatments except for V8 and R1 stages at S1 in third year of the study. Significant differences in N uptake for 2021 at S1 can be attributed to the fact that this site year had lower precipitation as compared to other site years, due to which the impact of irrigation treatments on N uptake was

more prominent. While in other site years sufficient water from precipitation was available to support N uptake. Hence N uptake was not limited by water application, such that recommended irrigation from all irrigation treatments was enough to maintain the ET required for crop production.

In 2019 at S1, highest N uptake at physiological maturity (R6 stage) was observed in the EPIC method of irrigation scheduling and this was the method in which the highest PWU was observed (Table 3 and 4). The lowest N uptake at R6 growth stage for 2019 at S1 was observed under CB method which corresponds to the lowest PWU (Table 3 and 4). In 2020 at S1, the lowest PWU was observed in SM that has the lowest N uptake at R6 growth stage, whereas both EPIC and IMA have higher N uptake and higher PWU as compared to SM method. Previous studies have also observed a positive relationship between water use and N uptake (Muschiatti-Piana et al., 2018; Quemada Miguel, 2016).

Table 4. Comparison of mean N uptake for maize across four different irrigation scheduling methods (SM, CB, IMA, EPIC) at V8, R1 and R6 growth stages for years 2019, 2020, and 2021 at Sand Plain Research Farm, Becker, MN (S1) and Rosholt Farm, Westport, MN (S2).

Site	Year	Growth stage	SM	CB	IMA	EPIC
S1	2019	V8	29.47 a	29.89 a	29.39 a	33.87 a
		R1	105.78 a	171.26 a	133.67 a	155.59 a
		R6	170.50 a	142.01 a	170.11 a	180.92 a
	2020	V8	42.23 a	42.96 a	41.92 a	39.05 a
		R1	139.61 a	152.71 a	124.50 a	164.97 a
		R6	196.37 a	218.21 a	211.99 a	219.90 a
	2021	V8	52.70 b	43.30 b	26.06 c	68.81 a
		R1	78.84 ab	66.67 bc	50.43 c	93.28 a
		R6	240.62 a	228.06 a	192.86 a	240.33 a
	Mean	V8	41.47 ab	38.72 ab	32.46 b	47.24 a
		R1	108.08 a	130.21 a	102.87 a	137.95 a
		R6	202.50 a	196.09 a	191.65 a	213.72 a
S2	2019	V8	111.45 a	112.27 a	108.73 a	116.29 a
		R1	163.62 a	137.78 a	157.78 a	121.78 a
		R6	184.50 a	233.43 a	209.49 a	203.84 a
	2020	V8	32.72 a	35.70 a	37.34 a	30.13 a
		R1	166.93 a	194.09 a	162.00 a	190.28 a
		R6	197.34 a	197.33 a	195.38 a	182.91 a
	2021	V8	40.88 a	32.911 a	37.84 a	43.65 a

	R1	91.38 a	69.47 a	65.64 a	73.78 a
	R6	217.59 a	232.70 a	247.19 a	238.59 a
Mean	V8	61.68 a	60.29 a	61.30 a	63.36 a
	R1	140.64 a	133.78 a	128.47 a	128.61 a
	R6	199.81 a	221.15 a	217.35 a	208.45 a

*N uptake (Kg/ha) values in the same row accompanied by the same letter are not significantly different ( $p < 0.05$ ) from each other*

However, in 2019 at S2, the CB method of irrigation scheduling resulted in maximum N uptake at physiological maturity (Table 4). Although it had lowest PWU, this treatment received maximum amount of irrigation and total water application (Table 3). Also, the CB method (and EPIC method) had significantly higher crop evapotranspiration for 2019 at S2. Hence, availability of more water to crop and its translation to higher crop evapotranspiration might be the reason behind higher N uptake in the CB method treatment. Similarly, in 2020 at S2 maximum N uptake at R6 stage is observed in both SM and CB method-based irrigation scheduling and these two methods received the highest irrigation in 2020 at S2.

In third year of the study at S1, SM and EPIC method of irrigation scheduling had higher N uptake. More frequent irrigations were observed for SM and EPIC methods which might have resulted in higher water availability for crop N uptake for these two methods. In general, as maize grows and advances towards higher growth stages, it accumulates more N in above ground biomass and hence total N (grain + stover) in plant biomass increases with increase in growth stage. In this study an increase in total N was observed from R1 to R6 growth stages for almost all treatments across all site years of the study. Although, unexpectedly, a decrease in N uptake was observed in CB method from R1 to R6 stage in 2019 at S1 and in EPIC method from R1 to R6 stage in 2020 at S2 (Table 4). This irregularity in N uptake may be attributed to small sample size of 6 plants per plot.

## Treatment effect on nitrate leaching

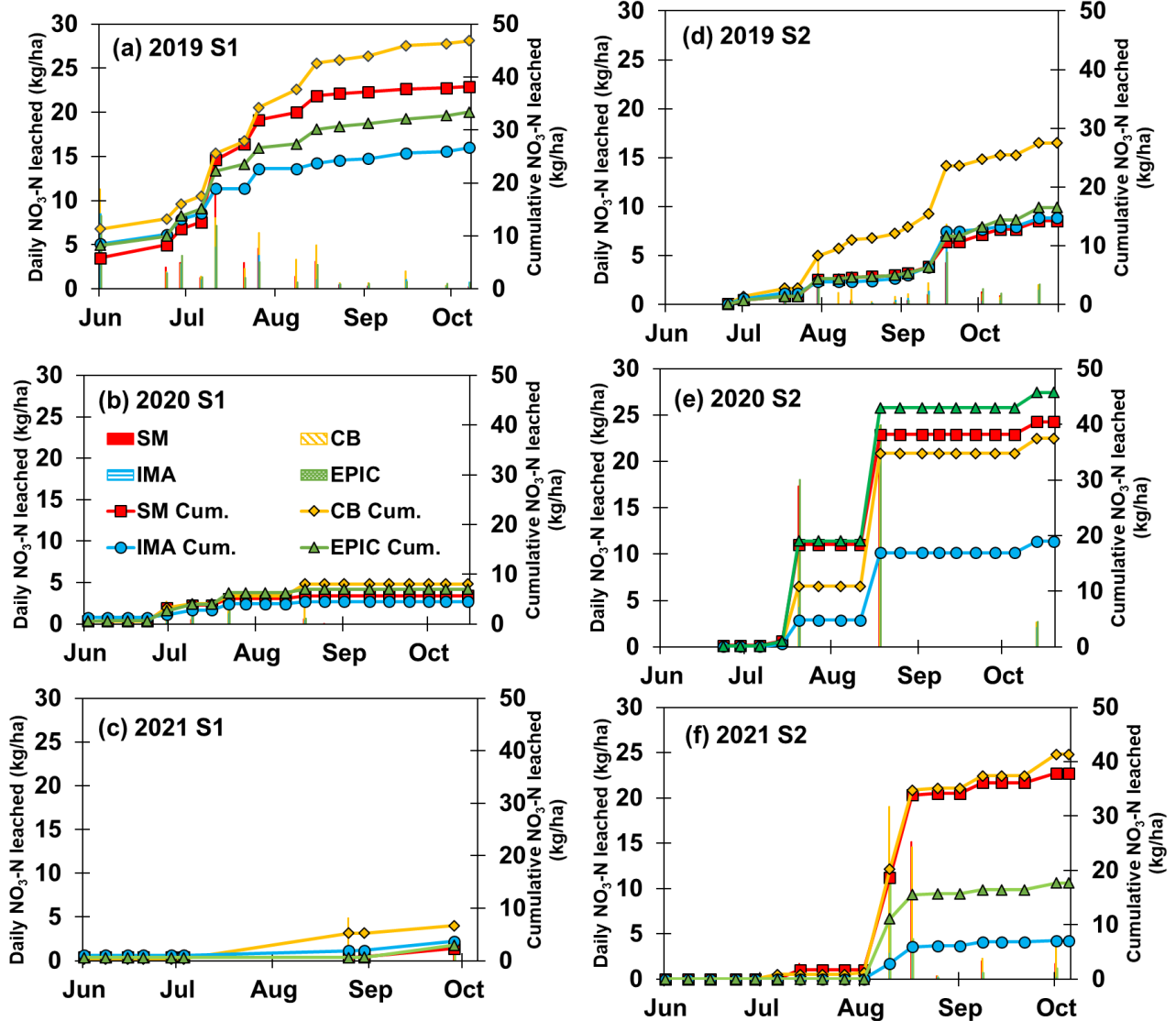


Figure 3. Daily and cumulative Nitrate-N leaching (kg/ha) for four irrigation scheduling methods (SM, CB, IMA, EPIC) for 2019, 2020 and 2021 growing season at site (a, b, c) S1 and (d, e, f) S2.

In this study nitrate concentrations in soil water samples varied from 0.1 mg/l to 210 mg/l across all site years. Total growing season nitrate-N leaching (load) varied from 2.37 Kg/ha to 46 Kg/ha with the minimum nitrate leaching (2.37 Kg/ha) occurring in the year 2021 for SM irrigation scheduling treatment at S1 and the maximum nitrate leaching for CB (46 Kg/ ha) irrigation treatment in 2019 at the same site S1 (Fig. 3a and 3c). Maximum growing season nitrate leaching on average for all treatments was observed in summer months from June to August which coincides with the time of supplemental irrigation applied and eventually higher total water application for all site years except for S2 in 2019 and S1 in 2021 (Fig. 3). In 2019 nitrate leaching

during the months of June to August was 93% and 36% of the total growing season nitrate leaching at S1 and S2 respectively. In 2020, it rose to 100% and 93% at S1 and S2 respectively and in 2021 it was 17% and 84% for S1 and S2 respectively. We observed that occurrence of irrigation events irrespective of the irrigation treatment contributed towards some nitrate leaching since all applied water is not translated to crop evapotranspiration, the portion of it that goes into deep percolation causes nitrate leaching. The results presented further in this section of the manuscript would aid in determining which irrigation treatments performed better to reduce this irrigation-induced nitrate leaching.

In 2019 at S1 (Fig. 3a), although the highest total irrigation amount (5.7 inch) was recommended by SM method of irrigation scheduling, CB method of irrigation scheduling resulted in maximum nitrate leaching (Table 5). This could be due to higher N uptake at physiological maturity (R6) for SM as compared to CB method (Table 4). Also, the differences in N-uptake and nitrate leaching between SM and CB methods may have been influenced by irrigation timing. Though both had similar seasonal irrigation amounts, the timing of irrigation was not the same. The EPIC model recommended more frequent irrigation events and lower irrigation amounts, leading to lower deep percolation thereby decreasing the nitrate losses. IMA on the other side recommended lower irrigation and resulted in lower nitrate leaching (Table 5). Other studies have also observed reduction in nitrate leaching with reduction in irrigation amounts (Bohman et al., 2020; Sigua et al., 2016). No significant difference ( $p < 0.05$ ) in nitrate leaching was observed among irrigation treatments in 2019 at S1, as nitrate losses were mainly caused by the precipitation events. Moreover, high precipitation followed by the irrigation event in wet years tend to increase the nitrate-N leaching losses. In 2020 at S1, no significant difference ( $p < 0.05$ ) in nitrate leaching was observed among irrigation treatments, however similar to 2019, highest leaching was observed under CB. In third year of the study, no significant differences were observed in nitrate leaching at S1 due to extremely low precipitation amounts, such that major portion of total water application was utilized by the crop (higher PWU) and not much of it was available for nitrate leaching. Hence, maximum PWU values and minimum nitrate leaching values were observed in 2021 at S1 for all irrigation treatments. Again, CB method had the highest nitrate leaching as compared to other treatments, though not significantly different. Overall, at S1, highest and lowest nitrate leaching was observed in 2019 and 2021 due to extremely wet and extremely dry years, respectively. Also, the relationship between irrigation and nitrate leaching was positive (increase in nitrate leaching with an increase in irrigation) in 2019 and 2020, whereas no increase in nitrate leaching was observed with an increase in irrigation in 2021 due to higher water uptake (Maharjan et al., 2014).

In 2019 at S2, precipitation amounts were higher than long term average for the region which resulted in lower irrigation amounts by each treatment as compared to other site years. The CB method of irrigation scheduling resulted in significantly higher nitrate leaching which corresponds to highest irrigation amount treatment. In 2020 at S2, EPIC model-based irrigation scheduling resulted in significantly higher nitrate leaching as compared to IMA, whereas nitrate leaching in EPIC was not significantly different from CB and SM methods (Table 5). Moreover, low N uptake

at physiological maturity (R6) was observed for EPIC method in 2020 at S2 (Table 4). The IMA method of irrigation scheduling resulted in lowest nitrate leaching as compared to other treatments, which can be attributed to lower irrigation recommendations. Therefore, nitrate leaching can increase with excessive irrigation amounts and can ultimately decrease crop N uptake.

Table 5. Cumulative Nitrate-N leaching for four irrigation scheduling methods (SM, CB, IMA, EPIC) for 2019, 2020, and 2021 growing seasons at Sand Plain Research Farm, Becker, MN (S1) and Rosholt Farm, Westport, MN (S2).

Site	Year	SM	CB	IMA	EPIC
S1	2019	38.17 ± 11.59 a	46.84 ± 2.53 a	26.68 ± 5.26 a	33.41 ± 7.29 a
	2020	5.72 ± 0.20 a	8.07 ± 1.71 a	4.54 ± 1.80 a	6.99 ± 2.46 a
	2021	2.37 ± 0.44 a	6.68 ± 4.50 a	3.72 ± 1.41 a	2.97 ± 0.90 a
	Mean	15.42 ± 16.14 a	20.53 ± 18.61 a	11.65 ± 10.63 a	14.46 ± 13.50 a
S2	2019	14.28 ± 4.00 b	27.49 ± 2.21 a	14.77 ± 2.09 b	16.52 ± 6.82 b
	2020	40.47 ± 20.51 ab	37.44 ± 14.11 ab	19.00 ± 2.34 b	45.70 ± 20.50 a
	2021	38.70 ± 7.69 a	42.66 ± 9.53 a	7.36 ± 8.66 b	18.07 ± 3.01 b
	Mean	31.15 ± 11.95 ab	35.86 ± 6.29 a	13.71 ± 4.81 b	26.76 ± 13.41 ab

*For each row, values for response variables accompanied by same letters suggest that they are not significantly different from each other*

In 2021 at S2, major precipitation events towards the end of growing season increased available water levels in SM and CB treatments resulting in significantly higher nitrate leaching for these treatments. Even though the EPIC treatment had the highest irrigation in 2021, nitrate leaching was lower as compared to CB and SM. One possible reason for low nitrate leaching could be higher frequency of irrigation and lower amount of irrigation per event in the EPIC method. In SM and CB methods, irrigation amounts per irrigation application were higher than EPIC because of which when heavy precipitation occurred in mid-august, most of the soil pores were filled with water and there was no room for extra water to be stored, resulting in heavy leaching. Whereas under EPIC, because irrigation application amounts per irrigation were smaller than CB and SM method, it resulted in higher  $ET_c$  which also made some room for precipitation to get stored in the soil profile which resulted in lower nitrate losses.

At S1, no significant difference in growing season nitrate leaching was observed among irrigation treatments due to extreme differences in precipitation for the three years of the study. Nitrate leaching was high in wet season (2019) and lower for dry seasons (2020 and 2021). High standard deviation in mean nitrate leaching values for S1 also confirms the role of precipitation and other climatic factors during the growing season. For S2, although the irrigation treatments had no significant differences in measured N uptake at physiological maturity, the CB method of irrigation scheduling resulted in significantly higher nitrate leaching while IMA method resulted in

significantly lower nitrate leaching on an average (Table 5). Therefore, the results of the study suggested that irrigation scheduling methods can significantly impact nitrate leaching without significantly impacting nitrogen uptake. Many studies have demonstrated a reduction in nitrate leaching with reduced irrigation (Bohman et al., 2020; Sigua et al., 2016). Some studies also found that the impact of irrigation is more prominent on nitrate leaching than the N fertilizer application rate (Pang et al., 1998).

### Treatment effect on grain yield and irrigation water use efficiency

Treatment averages for maize grain yield are summarized for S1 and S2 in table 6. Overall, no significant ( $p < 0.05$ ) difference in yield was observed among irrigation treatments within each site year and on average for S1, however, significant yield differences existed between treatments on average for S2. On average, at S1, 2019 and 2020 had 11% and 8% greater yields than 2021, respectively, which can be attributed to higher temperatures and lower precipitation in 2021 at S1 resulted in higher water stress and grain yield losses. Comparing irrigation treatments, no significant difference was observed between SM, CB, IMA and EPIC irrigation treatments at S1. For 2019 season at S1, reduction in IMA yield was 7%, 2.5% and 8% as compared to SM, CB and EPIC methods, respectively. In 2020, the variation in grain yield between treatments was less than 2019. There was no significant difference between treatments in 2019 and 2020. The yield reduction under IMA treatment was 3.2% as compared to CB treatment, with no difference when compared to EPIC and slightly greater yield in IMA as compared to SM in 2020. No significant difference in yield between irrigation treatments in 2019 and 2020 could be attributed to sufficient precipitation in these growing seasons resulting in soil water levels enough to support crop water requirements for all treatments. Grain yield varied more in 2021 as compared to 2019 and 2020. In 2021 at S1, a grain yield loss of 30%, 27% and 21% was observed under IMA when compared to SM, CB and EPIC methods, respectively. Significant losses in grain yield under IMA compared to other methods indicate that there is need to re-assess IMA based irrigation scheduling. Differences in grain yield between years can be attributed to the differences in climatic variables such as temperature, shortwave radiation, wind speed and precipitation coupled with irrigation magnitude and timing (Irmak, 2015).

At S2, on average, yield between all three years was significantly different with highest grain yield in 2021, followed by 2019 and then 2020. The grain yield at S2 in 2021 was 15% and 25% greater than 2019 and 2020, respectively. The yield difference between years can be attributed to total precipitation amounts received in that year. Even though 2021 was dry for most of the growing season, heavy precipitation was received after August 15<sup>th</sup> which resulted in higher total growing season precipitation in 2021 as compared to 2020 at S2. This shows that even the crop water use is usually reduced at the later stages of maize, additional precipitation can help in alleviating the water stress and increasing the crop yield. Comparing treatments, no significant difference in yield was obtained between SM, CB and EPIC, however, yield under IMA treatment was significantly lower than CB.

Relationship between irrigation and grain yield (irrigation yield production functions) for each site-year is presented in fig. 4. Though  $ET_c$  is more representative of crop water productivity as it is the direct representation of water losses from the field as a function of soil, water and crop management as well as climatic conditions (Irmak, 2015), developing irrigation-yield relationships are equally important in practice as they represent a direct concern to the irrigators, water management and regulatory agencies and irrigation professionals. In this study we found a linear relationship between maize yield and seasonal irrigation as described by Musick and Dusek (1971). From their research they observed that irrigation amount and grain yield can take linear or curvilinear forms in that the lower yielding treatments could be represented by a linear function and higher yielding treatments exhibit a curvilinear relationship. In this study we found that the wet 2019 and 2020 years have lower slopes than dry 2021 growing season at both sites which indicates lower dependence of grain yield on irrigation in wet years as compared to dry years. Though the linear relationship was stronger in 2019 ( $R^2 = 0.66$ ) and 2020 ( $R^2 = 0.89$ ) at S2, the increase in yield for every 25.4 mm or 1 inch increase in irrigation was 69% and 75% lower than 2021 at S2. At S1, grain yield and seasonal irrigation had a very weak negative linear relationship indicating no dependence of grain yield on irrigation. The relationship is strongest in 2021 with  $R^2$  of 0.95. In 2021 at S1, with every 25.4 mm or 1 inch increase in irrigation there is a 1.2 Mg/ha increase in yield. Similar results were obtained by Irmak (2015) where they observed greatest yield response to a unit irrigation applied during the two driest years of the six years study conducted in Nebraska.

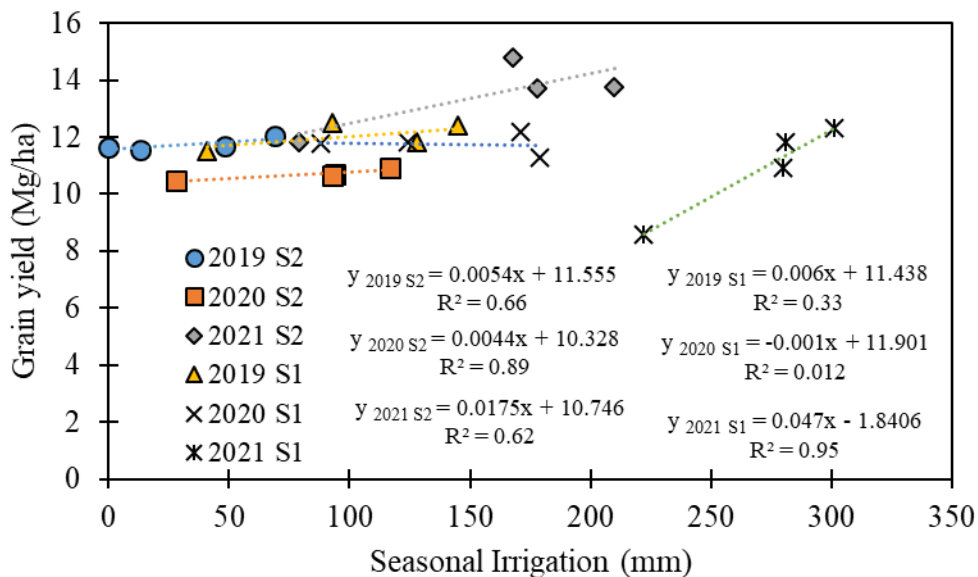


Figure 4. Maize yield response to seasonal irrigation for 2019-2021 at Sand Plain Research Farm, Becker, MN (S1) and Rosholt Farm, Westport, MN (S2).

Table 6. Maize grain yield, irrigation water use efficiency (IWUE) and crop water use efficiency (CWUE) for four irrigation scheduling methods (SM, CB, IMA, EPIC) for 2019, 2020, and 2021 growing seasons at Sand Plain Research Farm, Becker, MN (S1) and Rosholt Farm, Westport, MN (S2).

Year	Irrigation Treatment	Grain yield (bu/ac)	
		S1	S2
2019	SM	197 ± 11 a	180 ± 5 a
	CB	188 ± 6 a	183 ± 12 a
	IMA	182 ± 19 a	178 ± 12 a
	EPIC	199 ± 7 a	184 ± 8 a
2020	SM	180 ± 10 a	170 ± 6 a
	CB	194 ± 7 a	173 ± 6 a
	IMA	187 ± 5 a	166 ± 14 a
	EPIC	187 ± 16 a	169 ± 3 a
2021	SM	196 ± 28 a	217 ± 7 a
	CB	187 ± 15 a	235 ± 15 a
	IMA	137 ± 19 b	187 ± 22 a
	EPIC	173 ± 19 a	219 ± 12 a
Mean	SM	191 ± 7 a	197 ± 15 ab
	CB	190 ± 3 a	207 ± 20 a
	IMA	169 ± 23 a	182 ± 6 b

EPIC	187 ± 11 a	198 ± 15 ab
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*For each column, values for response variables for each year accompanied by same letters suggest that they are not significantly different ( $p < 0.05$ ) from each other*

### Soil water retention curves (SWRCs) using watermark sensors

Soil water retention curves (SWRCs) developed from watermark soil matric potential ( $\Psi_m$ -WM) and neutron probe volumetric water content ( $\theta_v$ -NP) measured during two corn growing seasons at 0.3, 0.6 and 0.9 meters are presented in Figure 9. Second-order polynomial regression equations were found to be the best fit at all three depths at 95% significance level ( $p < 0.05$ ) and a decrease in soil water content was observed with increase in soil water matric suction. Due to coarse texture of soils in both sites and low available water holding capacity, neutron probe measured soil water levels remained below 25% for all sites and depths. Also, this study was conducted in parallel with an irrigation management study and due to frequent irrigation (and precipitation) events, soil water levels rarely dropped too low ( $< 5\%$ ). Therefore, a large number of points fall within range of 10-25% volumetric water content measured by the neutron probe. Similarly, most of the soil matric suction values fall within range of 0-50 KPa as obtained by watermark sensors. These are also the typical irrigation range for the soil at the study site. All soil water retention curves had high R-squared values (Fig. 9)

Previous studies also indicate that the use of watermark sensors with site-specific SWRCs can be incorporated to enhance irrigation management (Varble & Chávez, 2011), while watermark sensors without site-specific calibration may still be used to improve irrigation for a specific soil, however, uncalibrated irrigation trigger points might have many limitations (Leib et al., 2003). In this study, Irrigation Trigger Points (ITPs) developed from measured data are presented in the next section that can aid in irrigation decision-making from watermark sensors.

### Irrigation trigger points using watermark sensors

Irrigation Trigger Points were derived from measured  $\theta_v$ -NP and  $\Psi_m$ -WM data. The soil matric potential values (taken as positive) obtained from a watermark sensor were averaged on a daily basis and neutron probe measured volumetric water content on that particular day was assumed to reflect volumetric water content corresponding to the watermark soil matric potential. Depletion in soil water content was obtained using the following formula:

$$\text{Depletion (in/ft)} = (\text{Field capacity (\%)} - \text{Volumetric Water Content (\%)}) * 0.12 \quad (7)$$

For watermark sensors the suggested range for irrigation trigger points is based upon 35% depletion of available water. Although it's upon the decision of irrigation manager to select the maximum allowable depletion for their crop. Table 7 shows the soil matric potential range and

corresponding depletion values (up to 70% depletion of available water) based in 2019 and 2020 growing season data.

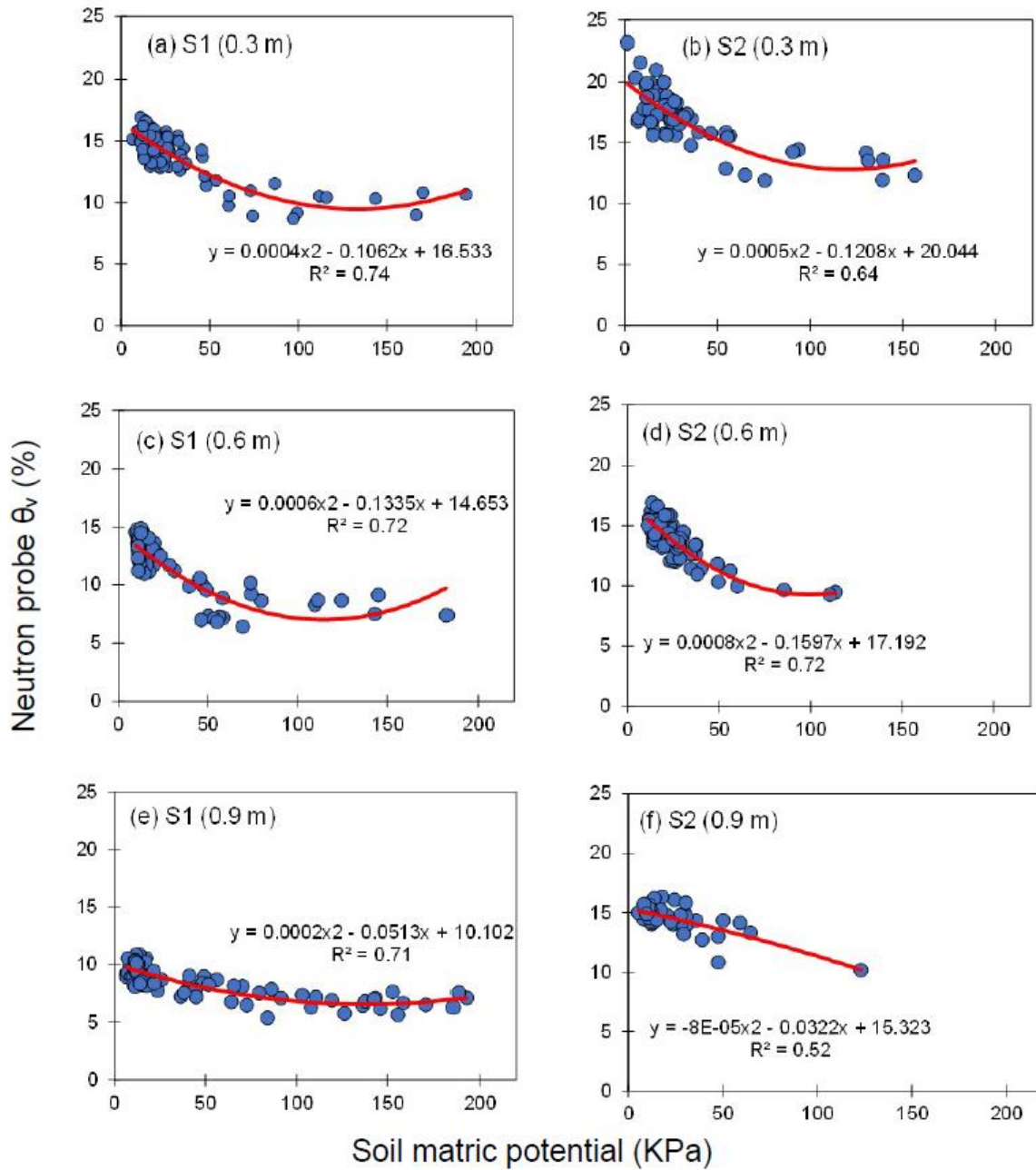


Figure 5. Soil water retention curves developed from soil matric potential data from watermark sensors and volumetric water content from neutron probe at 0.3, 0.6 and 0.9 meters soil depths for S1 and S2

Table 7. Depletion (cm/m) in available soil water holding capacity versus soil matric potential; available water holding capacity (AWHC); and irrigation trigger points (ITP) for soils at both sites

Soil matric potential (KPa)	Depletion (in/ft)	
	S1	S2
20	0.21 ± 0.08	0.31 ± 0.07
30	0.41 ± 0.09	0.47 ± 0.07
40	0.52 ± 0.09	0.54 ± 0.06
50	0.61 ± 0.04	0.62 ± 0.04
60	0.64 ± 0.08	0.67 ± 0.04
70	0.72 ± 0.04	0.84 ± 0.23
80	0.81 ± 0.04	0.89 ± 0.24
AWHC (in)	1.2	1.32
ITP (KPa)	30-45	30-45

## CONCLUSIONS

Overall, no significant differences existed in seasonal irrigation amount between SM, CB and EPIC whereas seasonal irrigation under IMA was significantly lower than other treatments. Highest and lowest irrigation was applied on average for all treatments for the 2021 (dry season) and 2019 (wet season) growing seasons respectively. Crop evapotranspiration was significantly ( $p < 0.05$ ) impacted by irrigation treatments. IMA method of irrigation scheduling resulted in significantly lower crop evapotranspiration in all site years and also on average for both sites. In general, higher PWU values were observed for EPIC and IMA treatments as compared to SM and CB treatments. N uptake was not limited by irrigation water application for any of the irrigation treatments studied. Since N uptake was not significantly ( $p < 0.05$ ) impacted by irrigation treatments at crop physiological maturity (R6 stage). Overall, all treatments maintained sufficient plant available water to support N uptake. A positive relationship between irrigation amounts and nitrate leaching was observed which is in accordance with previous studies (Bohman et al., 2020; Sigua et al., 2016). Nitrate leaching reduction of 62% was observed for IMA (lowest irrigation method) as compared to CB (highest irrigation method) at S2. However, the nitrate loss reduction in IMA method (lowest irrigation method) also incurred a grain yield loss of 12% in comparison to CB method at S2. No significant differences in grain yield were observed for CB, SM and EPIC treatments. Future work needs to be conducted on EPIC and IMA methods as these methods resulted in higher PWU and have shown potential for nitrate leaching reduction in low available water storage conditions and are less labor intensive.

## EDUCATION, OUTREACH, AND PUBLICATIONS

### ***Peer-Reviewed Journal Article***

1. Singh, G., Sharma, V. (Corresponding Author), Mulla, D., & Fernandez, F. Effect of irrigation scheduling methods on maize grain yield and nitrate leaching in Central Minnesota. *Transactions of the ASABE*. [Submitted: 2022]

### ***Poster***

1. Sharma, V., Singh, G., Mulla, D., Elvir, A. F., (Presenter), Fernandez, F. "Irrigation Management Impacts on Corn Yield and Nitrate leaching," AG EXPO 2022 Minnesota Corn Research and Promotion Council, Mankato, Minnesota, United States. (January 19, 2022). Invited.
2. Sharma, V., Singh, G., Fernandez, F. B., Mulla, D., Tahir, M. "Irrigation management impacts on corn yield and nitrate leaching." Minnesota Ag Expo 2020 Minnesota Corn Research and Promotion Council, Mankato, Minnesota, United States. (January 23, 2020). Invited.

### ***Presentation/Talk***

1. Sharma, V. "Irrigation and Nitrogen Management Research in Central Minnesota," Precision Irrigation Tour Irrigators Association of Minnesota, Becker, Minnesota, United States. (July 29, 2022). Invited.
2. Sharma, V. "Evaluation of four irrigation scheduling methods and their impact on corn production and nitrate leaching in the Central Sands Region," Minnesota Department of Agriculture- Clean Water Lunch and Learn Event Minnesota Department of Agriculture, Saint Paul, Minnesota, United States. (July 13, 2022). Invited.
3. Sharma, V. "Irrigation management for profitable corn production, water conservation, and ground-water quality protection," Department of Soil, Water, and Climate Spring seminar series 2022 University of Minnesota, Saint Paul, Minnesota, United States. (April 13, 2022). Invited.
4. Sharma, V. "Irrigation Research Update," 2022 Annual Irrigators Association of Minnesota Convention Irrigators Association of Minnesota, Freeport, Minnesota, United States. (February 17, 2022). Invited.
5. Sharma, V. "Irrigation Research in Minnesota," Irrigation and Nutrient Management Clinic East Otter Tail Soil and Water Conservation District, New York Mills, Minnesota, United States. (February 10, 2022). Invited.
6. Sharma, V. "Sustainable irrigation management: Research update," Sherburne County Lunch and Learn Sherburne Soil and Water Conservation District, Becker, Minnesota, United States. (November 30, 2021). Invited.
7. Sharma, V., (Advisor), Flores, A. E., (Presenter) "Irrigation management for profitable crop production and water quality protection," MASWCD Area II meeting MASWCD, Westport, Minnesota, United States. (September 14, 2021). Invited.
8. Sharma, V. "Irrigation Management for Profitable Crop Production and Water Quality Protection," Pope County Soil and Water Conservation District Rosholt farm field day Pope County Soil and Water Conservation District, Westport, Minnesota, United States.

(August 19, 2021). Invited.

9. Sharma, V. "Irrigation research and outreach in MN," Clean Water Council Policy Committee meeting Clean Water Council, Saint Paul, Minnesota, United States. (May 28, 2021). Invited
10. Sharma\*, V., Kjaersgaard\*, J. "Water Conservation Research," Bonanza Valley GWMA Advisory Team Meeting MN Department of Natural Resources, Saint Paul, Minnesota, United States. (March 24, 2021). Invited.
11. Sharma, V. "Irrigation management impacts on corn yield and nitrate leaching in Central Minnesota.," Pope County Soil and Water Conservation District Rosholt farm field day Pope County Soil and Water Conservation District, Virtual. (August 20, 2020). Invited.
12. Sharma, V. "Understanding the effects of irrigation and nitrogen fertilizer rates on crop water productivity and water quality," Pope County Soil and Water Conservation District Rosholt farm field day Pope County Soil and Water Conservation District, Virtual. (August 20, 2020). Invited
13. Sharma, V. "Profitable corn production and groundwater quality protection through advanced irrigation management," Department of Natural Resources, Monthly Water Appropriation meeting Department of Natural Resources, Virtual. (August 11, 2020). Invited.
14. Sharma, V. "Irrigation water management: Research methods and tools.," Irrigators Association of Minnesota 2020 field day Irrigators Association of Minnesota, Becker, Minnesota, United States. (August 4, 2020). Invited.
15. Sharma, V. "Irrigation and water quality research in Minnesota." Pope County Soil and Water Conservation District Irrigators Clinic Pope County Soil and Water Conservation District, Glenwood, Minnesota, United States. (March 10, 2020). Invited
16. Sharma, V. "Irrigation research in Minnesota," Sherburne County Lunch and Learn Event Sherburne County Soil and Water Conservation District, Becker, Minnesota, United States. (February 27, 2020). Invited.
17. Sharma, V. "Irrigation management for profitable crop production and water quality," 46th Minnesota Irrigators Association Annual Convention Minnesota Irrigators Association, Freeport, Minnesota, United States. (February 20, 2020). Invited.
18. Sharma, V. "Irrigation Research in Minnesota: Current and future needs," East Ottertail Irrigation and Nutrient Management Clinic 2020 East Ottertail Soil and Water Conservation District, New York Mills, Minnesota, United States. (February 11, 2020). Invited.
19. Sharma, V. "Irrigation management in Central Minnesota," W-4190 Water Policy and Management Challenges in a Water-Scare World. Annual 2019 Meeting University of Minnesota, Minneapolis, Minnesota, United States. (October 4, 2019).
20. Sharma, V. "Advanced Irrigation Management Strategies in Coarse-textured soils." Rosholt Farm Field Day Pope County Soil and Water Conservation District, Westport, Minnesota, United States. (August 27, 2019). Invited.
21. Singh, G., Sharma, V., Fernandez, F. G., Mulla, D. J., Tahir, M. "Evaluation and Performance of Different Irrigation Scheduling Methods and Their Impact on Corn Production and Nitrate Leaching in Central Minnesota," 2020 ASABE Virtual Annual conference. (July 13, 2020).

22. July 13-15, 2020
23. Singh, G., Sharma, V., Mulla, D., Fernandez, F., Tahir, M. "Impact of Irrigation Scheduling on Maize Grain Production and Nitrate Leaching in Central Minnesota," ASA-CSSA-SSSA International Annual Meeting 2022 ASA-CSSA-SSSA, Baltimore, Maryland, United States. (November 7, 2022).  
URL: <https://scisoc.confex.com/scisoc/2022am/meetingapp.cgi/Paper/146274>
24. Sharma, V., Singh, G., Mulla, D. J., Fernandez, F. G., Tahir, M. "Irrigation Management Impact on corn yield and nitrate leaching in Central Minnesota," ASA-CSSA-SSSA International Annual Conference 2020, Virtual. (November 9, 2020).

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