Title: Utilization of spatially precise measurements to autocalibrate the EPIC agroecosystem model

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A paper from the Proceedings of the
14th International Conference on Precision Agriculture
June 24 – June 27, 2018
Montreal, Quebec, Canada

Abstract. *Corn nitrogen recommendations for individual fields must improve to minimize the negative influence that agriculture has on the environment and society. Two adaptive N management approaches for making in-season N fertilizer recommendations are remote sensing and crop systems modeling. Remote sensing has the advantage of characterizing the spatial variability at a high spatial resolution, and crop models are prognostic and can assess expected additions and losses that are not yet reflected by the plant (e.g., due to recent management, weather, etc.). Remote sensing can be used to estimate crop biophysical parameters such as leaf area index or biomass, and can be used to calibrate crop systems models for making more accurate N fertilizer recommendations. A challenge in implementing this, however, is that an independent model calibration is required for each spatial area to be modeled. This study aims to test an autocalibration method at the sub-field scale for use in calibration of the EPIC (Environmental Policy Integrated Climate) model so it can be used more reliably for precision agriculture applications. EPIC is capable of simulating crop growth, nutrient transport and demand, and water movement on a daily time step. Following an initial calibration, an independent calibration is performed for each area within the study area using spatially precise outputs derived from remote sensing data (i.e., leaf area index and biomass). A field experiment was conducted in 2017 with four nitrogen rates and two timings of N fertilizer (i.e., preplant and V5 leaf stage). Tissue N and aerial imagery were collected at several days during the early growth stages to use as a basis for implementing and testing the autocalibration approach. The Monte Carlo algorithm was used to generate samples for the autocalibration step, and the Nash-Sutcliff efficiency was* *used as an objective function to analyze and interpret the results. The techniques utilized in this study serve as a framework for being able to use crop systems models for making more accurate N fertilizer recommendations.*

Keywords.
EPIC, crop model, autocalibration, fertilizer recommendation, remote sensing

Introduction:

Due to soil spatial variability and the unpredictable role that weather plays on soil and crop nitrogen dynamics, uncertainty in predicting optimal fertilizer nitrogen (N) rates for corn is high, and consequently, final recommendations for individual fields are less accurate than desired (Morris et al., 2018). Much attention is given to balancing the economic, environmental, and social pressures that influence N rate recommendations (Gourevitch et al., 2018). However, little is understood about how accurate N recommendations can be determined to properly quantify these pressures in the context of optimum N fertilizer rates, especially while accounting for spatial variability (both within and across fields). For producers that apply at least part of the crop N requirement during the season, the opportunity exists to apply the N fertilizer at a variable rate across space. The economic optimum N rate in corn typically varies spatially (Mamo et al., 2003; Scharf et al., 2006), so better matching fertilizer rate with crop requirement reduces the likelihood of N loss to the environment (Mulla, 2013). There are two principle techniques available for implementing an in-season adaptive N management approach – remote sensing and crop systems modeling. Each of these techniques has advantages and disadvantages when used as a tool for developing in-season N recommendations, but overall, both techniques have struggled to gain traction for use in a commercial setting because they each have practical limitations that have not yet been overcome (Thompson et al., 2015).

An advantage of spectral remote sensing for N rate predictions is that data covering a whole field can be collected quickly, so it is well-suited for quantifying the spatial variability due to N stress across a field (Franzen et al., 2016). However, because remote sensing is an indirect diagnostic technique for estimating crop biophysical phenomena, measurements inherently experience a delayed response compared to true biophysical indicators of nitrogen stress (e.g., tissue nitrogen content). For remote sensing data to be effectively utilized for making recommendations, practitioners must know the spectral thresholds for that specific crop so nitrogen fertilizer rates are adjusted appropriately. This is particularly challenging because data are typically normalized (e.g., via the nitrogen sufficiency index) and are expressed in relative units to account for external variables (e.g., growth stage, hybrid, radiometric inconsistencies, etc.), and can oftentimes seem arbitrary.

Optimum fertilizer N rates are difficult to determine as they depend on crop N requirement, soil-derived N supply due to net mineralization and immobilization, and losses of N via leaching, denitrification, and volatilization. Crop systems models can be used to simulate these N cycle transformations and processes, and can be used as a management tool to determine in-season crop N status so N fertilizer rates match crop N demand. Crop systems models also have the advantage of being prognostic, so they can assess expected additions and losses that are not yet reflected by the plant (e.g., due to recent management, weather, etc.). However, uncertainties arise due to limitations in the accuracy of available input data, especially soils information. For crop model outputs to be reliable, the models must be calibrated using observations or empirical estimation of soil and plant parameters throughout the season. Calibration of models is a crucial step for improving model reliability and gaining accurate insights, but it is oftentimes challenging to collect sufficient calibration data in a production environment, especially while accounting for spatial variability that exists across a field. A major limitation of using crop systems models for making N fertilizer recommendations is that most models assume a homogeneous simulation area. Furthermore, it is typically the case that input data and model parameters vary in scale, and therefore cannot effectively account for spatial variability at the required scale without additional calibration.

Scale of Data Inputs

When input data from different scales are utilized together in a crop systems model, data aggregation typically occurs, which can lead to substantial uncertainty if calibration at the smallest scale is not performed (Porwollik et al., 2017). It is also common to apply a model to a larger extent than it is calibrated for by implementing it many times across an area using unique inputs and parameters representing each spatially homogenous area. The major barrier to this method, however, is the availability of accurate input data and model parameters at the desired spatial resolution. It is often necessary to use soils data from the Soil Survey Geographic Database (SSURGO) for precision agriculture applications, even though data were collected and are intended to be used at a minimum scale of 1:24,000 (much coarser scale than most precision agriculture applications require). Ideally, input data used in a model for characterizing an output should be at a similar or finer scale than the variability of that output. For example, because it is common that the economic optimum N rate in corn varies spatially within a field (Mamo et al., 2003; Scharf et al., 2006), it may be of interest to use a model to characterize the economic optimum N rate based on crop N uptake. Input data should be of fine enough scale to capture the spatial variability of crop N uptake so uncertainty is minimized. Indeed, the use of site-specific calibration parameters (instead of default values) minimizes errors across different soil, water, and nutrient conditions (Sinnathamby et al., 2017). However, a barrier to implementing an additional, site-specific calibration method at a scale similar to the spatial variability of the predicted parameter is the tedious effort required to perform the calibration itself. Autocalibration methods have been used to address this challenge, but they have only been tested at the farm scale and larger (Kamali et al., 2018; Sinnathamby et al., 2017; Xiong et al., 2014).

A major inherent limitation of the EPIC (Environmental Policy Integrated Climate) model for variable rate N applications is that maximum leaf area index (LAI) estimations are not inherently affected by N fertilizer rate (Salo et al., 2016). This is an issue if EPIC is used for precision N management because it does not consider how crop N uptake affects LAI. By calibrating EPIC based on estimated in-season LAI and biomass from remote sensing, this limitation can be overcome. The objective of this work is to implement and test an autocalibration method at the sub-field scale for use in calibrating the EPIC crop systems model based on in-season estimates of LAI and biomass for precision agriculture applications, specifically for predicting crop N availability.

Materials and Methods:

Site Description

A field study was conducted at the Agricultural Ecology Research Farm at the Southern Research and Outreach Center near Waseca, MN in 2017 to evaluate the ability to autocalibrate the EPIC model during the growing season based on site-specific characteristics and N fertilizer management. Measured data were collected from a 0.67 ha area of the field having a subsurface tile drainage system at a depth of 1.2 m and drain spacing of 24 m. There were two soil types within the study area: the Webster clay loam (fine-loamy, mixed, superactive, mesic Typic Endoaquolls) and the Nicollet clay loam (fine-loamy, mixed, superactive, mesic Aquic Hapludolls). The Webster series is poorly drained and is located on the broad, more level areas of the landscape, whereas the Nicollet series is somewhat poorly drained and is located on more convex landscape areas. Both the Nicollet and Webster soil series have a group C hydrologic classification. The boundary delineating the two soil types is roughly similar to the boundary between the two replications (one replication had the Webster series as the predominant soil type, and the other had the Nicollet; Figure 1).

The study area was comprised of 16 individual treatment plots (30 m x 14 m). Four N fertilizer rates (0, 67, 135, and 202 kg N ha^{-1}) were applied at either preplant or the V5 growth stage for a total of 6 treatments (Table 1). Fertilizer N was broadcast applied as urea for both preplant and sidedress application timings. Preplant fertilizer was applied to all treatment plots and consisted of 50 kg ha^{-1} P_2O_5 (as triple superphosphate), 67 kg ha^{-1} K_2O (as potash), and 10 kg ha^{-1} SO_4^{-2} (as gypsum). Refer to Table 2 for the dates of other field operations.

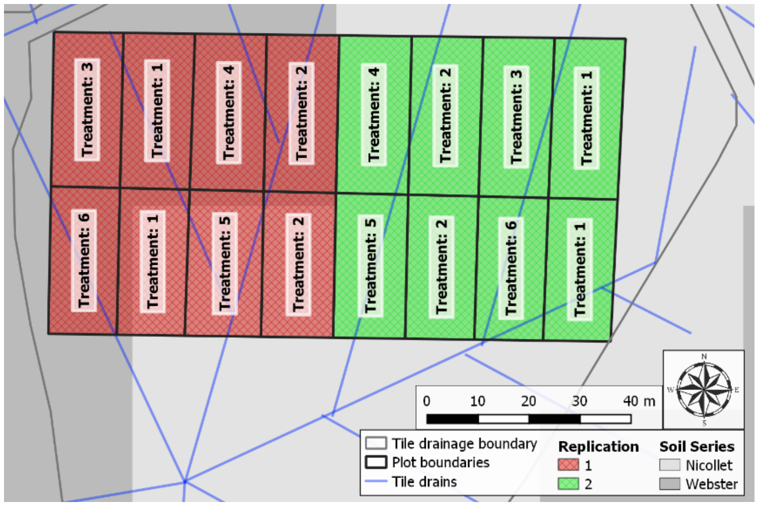

Figure 1: Map of the treatment plots, soil types, and treatment information.

Table 1: Nitrogen (N) fertilizer treatment rates (kg N ha^{-1}).

Treatment	Preplant N (kg ha^{-1})	Sidedress N	Total N
1	0	0	0
2	67	0	67
3	135	0	135
4	202	0	202
5	67	67	135
6	135	67	202

Table 2: Dates of 2017 field operations.

Date	Field operation
May 8	Preplant fertilizer
May 10	Preplant nitrogen
May 11	Tillage (field cultivator)
May 12	Planting
Jun 19	Sidedress nitrogen
Nov 8	Harvest

EPIC Model Description

The EPIC (Environmental Policy Integrated Climate) model is a site-based, agroecosystem model capable of simulating crop growth, nutrient transport and demand, and water movement (Izaurralde et al., 2006; Williams, 1990), and was used in this study. EPIC was originally developed to assess the effects of soil erosion on overall productivity (Williams et al., 1989), but more recent versions have been developed to incorporate hydrologic and nutrient cycling components and have been used to estimate nutrient losses from fertilizer applications (Chung et al., 2001; Phillips et al., 1993). It simulates soil and crop-related processes for a specific site, and operates on a daily time step. It is especially attractive to be used as a decision support tool for in-season N management because it has a strong hydrologic component and considers many of the major soil N dynamics and processes that affect crop N availability and growth (Salo et al., 2016). Furthermore, it supports a rather complex combination of management operations (e.g., tillage, irrigation, fertilization, etc.) and rotations, making it a more robust model overall (Cassman et al., 2002). EPIC was used in this study to estimate crop N availability for developing more accurate sidedress N fertilizer recommendations.

The EPIC model simulates daily gains in crop biomass based on the concept of radiation-use efficiency whereby a proportion of photosynthetically active radiation is assumed to be intercepted by the plant canopy and is converted into plant biomass (Stockle et al., 1992). As the growing season progresses, daily crop growth and yield potential are affected by ambient vapor pressure, CO_2 concentration, and the most severe of daily calculated indices for water, temperature, N, phosphorus, or aeration stress. A fraction of daily biomass accumulation is partitioned to roots, whose growth is affected by temperature, soil strength, and aluminum content. Daily weather can be input or estimated based on long-term monthly averages; whether input or estimated, required parameters include precipitation, air temperature, solar radiation, wind, and relative humidity. Dozens of physical and chemical soil properties for each soil layer drive the nutrient transport processes in EPIC. The hydrologic processes supported by EPIC include surface runoff, infiltration, evapotranspiration, tile drainage, percolation, lateral subsurface flow, soil water content dynamics, and water table dynamics. Soil temperature in each soil layer is computed daily according to equations described by Potter and Williams (1994), and is an important parameter in the nutrient cycling and hydrology subroutines. Soil organic C is simulated by subroutines that convert organic materials into one of three compartments, each having a different turnover time: microbial biomass (days or weeks), slow humus (few years), and passive humus (hundreds of years). Tillage subroutines simulate the mixing of nutrients and crop residues within the plow layer, and also simulate changes in bulk density, crop residues, surface roughness, and ridge height (Izaurralde et al., 2006).

In this study, i_EPIC/i_EPIC_console were used to interface and manipulate EPIC inputs and outputs located in a PostgreSQL database and raw text-based EPIC files (EPIC version 1102 was used). i_EPIC is a Windows based program for interacting with EPIC. Its two primary purposes are: i) to control and automate large numbers of EPIC runs, generating input, repeatedly invoking EPIC, and cataloging the results; and ii) to provide easier-to-use interfaces for building EPIC input and tabulating EPIC output (Gassman et al., 2003).

Model Inputs

Soil samples were collected at the beginning of the 2016 growing season for the surface 15 cm and included analyses for pH, organic matter content, and P, K, and NO_3^- concentration. Soil properties that were not directly sampled were obtained from SSURGO available from the Natural Resource Conservation Service (NRCS). These inputs include layer depth, bulk density, wilting point, field capacity, percentage sand, percentage silt, organic carbon content, calcium carbonate content, and cation exchange capacity. Weighted averages for each soil property were calculated for each layer across all components of the soil map unit. The dominant component was used to determine the layer thicknesses for aggregating across other components. For this study, daily precipitation, maximum and minimum air temperature, relative humidity, solar radiation, and wind speed were measured within 300 m of the study area. The Penman-Monteith method (Monteith, 1965) was used to estimate the potential evapotranspiration. Dates of field operations that took place throughout the growing season were input into EPIC and are shown in Table 2.

Field Sampling

Crop nitrogen uptake was measured at the V5, V10, and R2 growth stages, and grain yield was measured at physiological maturity. The V5 sampling occurred on 15 June, which was four days prior to the sidedress N application (Table 2). EPIC model simulations were performed independently for each treatment with and without in-season calibration via integration of nitrogen uptake predictions from remote sensing data. Aerial imagery was collected to be used as a site-specific calibration input. Nitrogen uptake observations and predictions were used to calculate the root mean squared error, which was subsequently used to evaluate the performance of the integrated approach.

Remote sensing

Hyperspectral aerial images were captured with a gimbal-stabilized Pika II line-scanning hyperspectral camera (Resonon, Inc.; Bozeman, MT) mounted on an unmanned hexacopter (DJI Matrice 600 Pro, Nanshan District, Shenzhen, China). DJI Ground Station Pro (iPad app) was used to create and execute flight plans for controlling altitude, heading, and ground speed. Ground sampling distance for images at various dates ranged from 2.5 cm to 6.0 cm. Gray reference panels with known reflective properties were placed in the study area prior to image capture; panels were 60 x 60 cm and the surface was 50% BaSO4/50% gray paint by weight. Radiometric correction was performed via SpectrononPro software (Resonon, Inc.; Bozeman, MT) using a calibration file provided by Resonon for the specific camera and lens that were used. Gray reference panels that were placed in the study area prior to image capture were used to convert spectral radiance to surface reflectance across all images. Methods describing postprocessing steps, spectral analysis, and LAI and biomass sampling is described in Nigon et al. (2017). The Improved Modified Chlorophyll Absorption Ratio Index (MCARI2) was used to predict LAI and biomass during the early growth corn growth stages. MCARI2 uses green, red, and near-infrared bands to incorporate a soil adjustment factor while preserving sensitivity to LAI and resistance to chlorophyll influence. It has been shown to be a good predictor of green LAI (Haboudane et al., 2004).

Sensitivity Analysis and Calibration

A preliminary sensitivity analysis was performed to identify the inputs and model parameters that were most sensitive to outputs related to hydrology, N cycling, and crop growth (i.e., LAI, grain yield, and biomass). Initial default values were assigned to model inputs and parameters that were most sensitive to outputs based on results of the preliminary sensitivity analysis. Default values were chosen based on how they influenced the outputs. Values were chosen so that EPIC was able to model outputs related to the water balance, nitrogen balance, and overall crop growth that seemed to be reasonable for the site.

Because EPIC is process-based, the initial model calibration was performed in an iterative fashion based on comparisons between measured and simulated values for a subset of EPIC inputs and parameters that have an influence on hydrology, N cycling, and crop growth. During this initial calibration, only the EPIC outputs that lack spatially precise measured values were calibrated. These included evapotranspiration, tile drain flow, and tile drain nitrate loading.

Following the initial calibration steps, EPIC outputs that have spatially precise measured values were calibrated for each individual homogeneous area of the field. These included LAI, biomass, and total N uptake estimated from in-season remote sensing, as well as grain yield at the end of the season. In this context, homogeneous refers to an area of the field that either has input data aggregated to a minimum spatial scale, or that has input data collected at a minimum spatial scale. The minimum spatial scale used in this study was the size of the treatment plots (i.e., 30 m x 14 m). Because it is tedious to calibrate the model for several measured inputs across many spatially homogenous areas of a field, it is desirable to implement an autocalibration technique.

In this study, the SPOTPY Python package (Houska et al., 2015) is being investigated as a tool to perform the autocalibration. SPOTPY is a pure Python implementation that enables the use of computational optimization techniques for calibration, uncertainty, and sensitivity analysis techniques of any environmental model that is able to be run within the SPOTPY class and whose inputs and outputs can be manipulated by SPOTPY. Upon linking SPOTPY to the input and output tables that EPIC utilizes, SPOTPY utilizes the following steps to implement a generalized autocalibration procedure: i) choose an algorithm to fit model outputs to observed data (the Monte Carlo algorithm was used in this study), ii) run the model an adequate number of times so that there are a sufficient number of iterations to generate reliable results, and iii) choose an objective function to analyze and interpret the results (Nash-Sutcliff efficiency; NSE) was used in this study. Note that implementation of SPOTPY is still a work in progress, so results are not ready to be included in these proceedings.

Results and Discussion

Tissue N concentration decreased as the season progressed, indicating a dilution in N concentration due to a rapid increase in vegetative growth (Figure 2). At the V5 stage (four days prior to sidedress N application), the 0 kg N ha^{-1} treatment already had a lower tissue N concentration than any of the other treatments. All fertilizer N was applied to treatments by the V10 stage, and by this point, both the 0 and 67 kg N ha^{-1} treatments had lower tissue N than the higher rates. There was more variability in tissue N at the R2 growth stage, but there was not a statistical difference among treatments that had at least 135 kg N ha^{-1} applied. The study site had two different soil types (Figure 1), and this likely contributed to the variability observed at any of the growth stages.

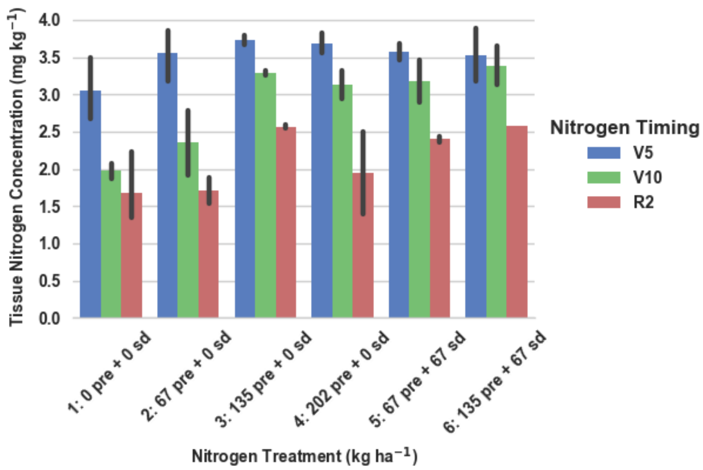

Figure 2: Tissue nitrogen concentration at the V5, V10, and R2 growth stages. Labels on the x-axis refer to treatment number and also denote preplant and sidedress N fertilizer rates (labeled “pre” and “sd”, respectively). Error bars represent 95% confidence intervals.

An exponential curve best modeled the relationships between MCARI2 and each of the measured biophysical parameters (Figure 3). MCARI2 had a better relationship with above-ground biomass (R^2 = 0.57) than with LAI (R^2 = 0.46). Nigon et al. (2017) used the exponential models described in Figure 3 to predict each of the biophysical parameters, and they reported root mean square error (RMSE) values of 4.70 g and 0.31 for biomass and LAI, respectively. Most of the variability occurs during the later growth stages, especially for LAI. Although the ability of the MCARI2 spectral index to predict biomass and LAI is not perfect, it does seem to be a viable option to be used as a calibration parameter for the EPIC model. It is important to consider the variability of such estimations when interpreting the results of the model, however. Further analysis is required to determine if other band combinations and/or classification techniques can be implemented to reduce the error in biomass and LAI predictions.

Table 3: EPIC inputs and parameters most sensitive to outputs related to hydrology, nitrogen cycling, and crop growth.

EPIC Input Code	Description	Hydrology	Nitrogen Cycling	Crop Growth	Default Value
Crop Development					
BN1	Nitrogen uptake at emergence	x		x	0.044
BN2	Nitrogen uptake mid-season	x		x	0.025
BN3	Nitrogen uptake at maturity		x	x	0.013
CAF	Critical aeration factor	x	x	x	0.85
DLAI	Growing season leaf decline		x	x	0.85
DLAP1	Leaf development first point	x	x	x	15.05
DLAP2	Leaf development second point	x	x	x	50.95
DMLA	Maximum LAI			x	6
TBSC	Minimum temperature	x		x	10
TOPC	Optimal temperature	x		x	25
WA	Biomass energy ratio		x	x	45
Parameters					
PARM(2)	Root growth:soil strength	x		x	1.2
PARM(17)	Vertical crack flow coefficient	x			0.25
PARM(30)	Denitrification trigger		x		1
PARM(35)	Water stress weighting coefficient			x	0.5
PARM(42)	NRCS curve number index coefficient	x	x		0.5
PARM(53)	Microbial activity coefficient		x	x	0.9
PARM(73)	NRCS curve number upper limit	x	x		1.5
PARM(74)	Penman-Monteith coefficient	x	x		1
PARM(95)	Soil temperature damping depth		x	x	1
Soils					
BD	Bulk density		x		1.04
CNDS	Nitrate concentration		x		8.3
FC	Field capacity	x	x		0.32
WOC	Organic carbon		x		2.75
WTMN	Minimum water table depth	x	x	x	1.2

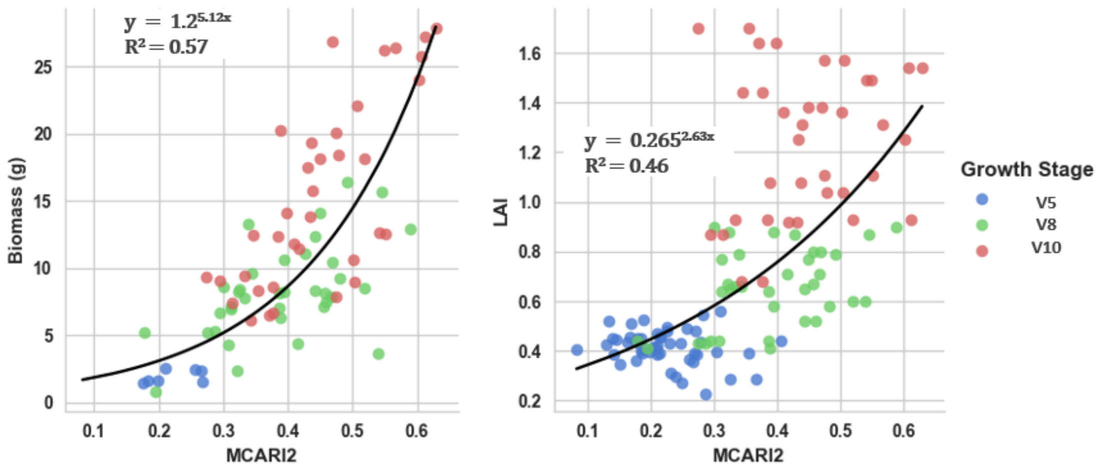

Figure 3: Relationship between MCARI2 (Modified Chlorophyll Absorption Ratio Index) and biomass (left) and MCARI2 and leaf area index (LAI; right) during early growth stages of corn development (data adapted from Nigon et al., 2017).

At this point, model calibration results are not available due to difficulties in properly setting initial EPIC inputs and parameters in order to obtain realistic water and N balances. Although we have encountered challenges, we are optimistic that we will get past this obstacle soon and have autocalibration results to share at the time of the conference.

Summary

Results from this study illustrate that simple relationships between spectral remote sensing information and early season crop biophysical parameters can be used to estimate the spatial variability of those parameters across a field. This information can subsequently be used to calibrate crop systems models that attempt to make in-season N fertilizer recommendations. There is still much work to be done to properly evaluate the autocalibration approach described herein, but we are optimistic that the techniques utilized in this study will serve as a framework for using crop systems models for improving the accuracy of N fertilizer recommendations.

Acknowledgements

The MnDRIVE Initiative provided financial assistance for this work via the Global Food Ventures Fellowship and the partnership with the University of Minnesota Informatics Institute.

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