Combining crop simulation model and remote sensing tools for in-season nitrogen management in corn

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Introduction

Nitrogen (N) is crucial for corn (*Zea mays* L.) growth, development, and yield (Sinclair and Horie, 1989). Managing soil N supply for optimum corn growth is a challenge due to N losses, variation in soil properties and weather conditions, differences in corn hybrids, and N requirement among growth stages

(Mamo et al., 2003; Scharf et al., 2005; Dhital and Raun, 2016). Since N is typically the most yield-limiting nutrient, growers usually apply more than enough N fertilizer to maximize corn grain yield (Sela et al., 2016). This excess N application has economic, health and environmental consequences such as contamination of ground and surface waters and greenhouse gas emissions (Andraski et al., 2000; Shcherbak et al., 2014; Venterea et al., 2016). Greater than 70% of N and phosphorus load into the hypoxic zone of the northern Gulf of Mexico comes from agriculture, with more than 50% attributed to corn and soybean production (Alexander et al., 2008). Since corn and soybean (*Glycine max* L.) are the dominant crops in the midwestern United States, it is of no surprise that many watersheds of the Upper and Central Mississippi River Basin have the greatest nutrient loads (NAWQA/USGS, 2014).

As a part of the Midwest, Minnesota is within one of the most intensive agricultural areas in the United States, where corn is cultivated using high level of nitrogenous fertilizer under conventional cropping practices. As such, the N fertilization is causing nitrate pollution in ground and surface waters, that has been considered as a growing threat to Minnesota`s drinking water (MEQB, 2015). Nevertheless, corn alone contributes about 50% of the total $10.3 billion value of the state's agricultural crops and is the backbone of the agricultural industry in Minnesota (USDA/NASS, 2016). Therefore, efforts towards efficient N fertilizer use for sustainable corn production are extremely important.

Several methods have been developed to determine the N requirements of corn for efficient N fertilizer use. These methods are based on mass balance (yield goal), yield response function and corn-fertilizer price (maximum return to N; MRTN), soil (pre-plant, pre-sidedress and Illinois soil N tests), crop sensing (chlorophyll meter reading and remote sensing) and crop modeling. Since the 1970s, expected yield or yield goal estimate (Stanford, 1973) has been a major determinant for economically optimum N rate recommendation. In this approach, the expected yield goal is multiplied with the N removal rate (12kgN/t) to determine the N requirement of corn (IPNI, 2012). The final fertilizer N rate recommendation is made after subtracting N credits from residual soil N, manure and previous legume credits. This method is easy to implement but is a generalized approach that assumes a linear relationship between N rate and yield over diverse growing conditions. Since soil N availability depends on the soil-water-plant system and varies spatially and temporally, yield-goal based N rate recommendations often have poor correlation between yield-based N rate and final yield (Vanotti and Bundy, 1994; Lory and

Scharf, 2003). Also, accurate yield goal estimation for a given soil is difficult as it varies from year to year depending on environmental conditions. More recently, MRTN, a data-driven recommendation method based on multi-location and multi-year field trials, has been used in major corn producing states (Nafziger et al., 2005). The optimum N fertilizer rate is based on a quadratic-plateau response of grain yield to N rate and the relative prices of N fertilizer and corn. This generalized method is adaptable with changing economic condition but it does not address spatial variability in soils or inter-and intra-seasonal weather variation affecting N use in corn (Melkonian et al., 2008). Usually, the soil-test based methods are not used as the sole approach for N recommendations, but as supplement to other methods such as the yield-based and the MRTN.

Plant-based crop sensing methods, such as chlorophyll measurements and remote sensing have also been used to make N recommendations in corn. Chlorophyll meter readings are used to determine the chlorophyll content in leaves which is associated with N content. This approach usually requires a high-N reference strip in the field to make N recommendations when the meter reading is less than 95% of the high-N reference strip values (Peterson et al., 1993). Several remote sensing devices, such as multi-spectral and hyperspectral sensors, are used to estimate crop N-status in a field. These sensors, when mounted on aerial platforms can cover a large area of a field and can give rapid identification of N sufficient and deficient areas in a field through a non-destructive procedure. However, remote sensing based approaches also require high-N reference strips to make N-rate recommendations (Bausch and Duke, 1996; Kitchen et al., 2010; Scharf et al., 2011). Such reference strips might not be the representative area of the whole field, which could result in excess or inadequate fertilization in some areas. Also, N rate recommendation from remote sensing is solely based on crop N status and does not account for soil N. Crop simulation models are powerful tools to predict crop growth, development, and yield as a function of cultivar, soil, weather and agronomic management. Crop models have been widely used to assess crop response to stress, changing climatic conditions and evaluate management options such as irrigation and N fertilization recommendations. The major limitation of crop models for N rate recommendations has been the lack of site-specific information on model inputs for calibration and spatial variability as simulation assumes homogenous units due to the same model inputs (Thorp and Bronson, 2013).

<u>New Approach for In-season N Rate Recommendation</u>

Overall research question: How can we improve in-season N rate recommendation in corn taking into account the site-specific N status of the soil-crop system, temporal variation in weather and the effects of cultivar and management practices?

We will conduct research to improve the in-season N rate recommendation in corn by addressing the above-mentioned limitations/challenges. I propose a new approach to the problem that includes the combining of crop simulation models and remote sensing.

Crop growth, development, yield, and soil N status can be simulated on a daily basis using crop models. The effects of cultivar, soil, weather conditions and agronomic management practices are considered in the simulations. Remote sensing has an advantage of rapid, site-specific estimation of crop bio-physical parameters such as biomass, leaf area index and canopy N content across spatial scale. This advantage can be used to calibrate, update, optimize the model inputs and re-estimate missing information in crop models across spatial scales (Delécolle et al., 1992; Guérif and Duke, 2000; Launay and Guerif, 2005).

My research project is based on the hypotheses that the integration of crop simulation models with remote sensing data will (i) consider the effects of cultivar, management practices, spatial variability in soil and crop, and temporal variation in weather for N rate recommendation. (ii) optimize/update the model inputs and enhance the prediction accuracy of N status of the soil-crop system across temporal and spatial scales and thus will help to better determine optimum N rates across a field.

Research Projects, Materials and Methods

Projects consisting of plot- and field-scale studies were started during the 2016 growing season. The overall objectives of these projects are to (i) evaluate the performance of the crop model (CERES-maize) to simulate corn growth and soil N content at different growing conditions (ii) assess the robustness of remote sensing based vegetation indices to estimate corn growth and N content at diverse growing environments and (iii) to assimilate remote sensing data into the CERES-Maize model to predict spatio-temporal variation in soil-crop N status.

The plot-scale study is conducted at three University of Minnesota Research and Outreach Centers (Waseca, Lamberton and Grand Rapids), representing a range of soil type, precipitation and temperature gradients. The experimental plot is under corn-soybean cropping system. The experiment is configured as a randomized complete block design with four replications in Waseca and Lamberton and three replications in Grand Rapids. Treatments include N rates of 0, 80, 100 and 120% of university guidelines at each location. Plant data collection includes phenology observation, plant height, leaf area index, chlorophyll content, above ground biomass and N content every 10 to 14 days at each location. At harvest, total grain yield, stover dry matter, cob dry weight, and harvest index are measured. Soil samples are collected from the 0- to 30- and 30- to 60-cm depths at one week before planting and at the eight-leaf collar and tassel stage for total N and organic matter. Soil samples are collected at 30-cm intervals to a depth of 120 cm after harvest for soil nitrate-N content. In 2017, images of the plots will be taken utilizing a Tetracam RGB+3 (Tetracam Inc., CA) multispectral camera mounted in an unmanned aerial vehicle.

The field-scale study is being conducted at the University of Minnesota Southwest Research and Outreach Center located in Lamberton. Treatments include a control with no N application and a treatment with 240 kg N/ha applied at six-leaf collar stage in randomly assigned strips. Soil samples are collected in grids at the geo-referenced points from the 0- to 30- and 30- to 60- cm depths before planting for total N, phosphorus, potassium, organic carbon, cation exchange capacity, pH and soil texture. Soil samples are also collected (0-30 cm depth) at the eight-leaf collar stage for total N and organic matter content. Satellite imagery of the field from RapidEye (Level 3A) products are used for this study.

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