A CROP AND SOIL STRATEGY FOR SENSOR-BASED VARIABLE-RATE NITROGEN MANAGEMENT

D.F. Roberts

Department of Plant and Soil Sciences
Mississippi State University
Mississippi State, Mississippi

J.F. Shanahan

Agroecosystem Management Research Unit
USDA-ARS
Lincoln, Nebraska

R.B. Ferguson

Department of Agronomy and Horticulture
University of Nebraska-Lincoln
Lincoln, Nebraska

V.I. Adamchuk

Department of Biological Systems Engineering
University of Nebraska-Lincoln
Lincoln, Nebraska

N.R. Kitchen

Cropping Systems and Water Quality Research Unit
USDA-ARS
Columbia, MO

ABSTRACT

Crop-based active canopy sensors and soil-based management zones (MZ) are currently being studied as tools to direct in-season variable-rate N application. Some have suggested the integration of these tools as a more robust decision tool for guiding spatially variable N rates. The objectives of this study were to identify (1) soil variables useful for MZ delineation and (2) determine if MZ could be useful in identifying field areas with differential crop response to N and hence be effective in guiding spatially variable N applications in addition to crop canopy sensing. Eight N rates (0 to 274 kg ha^{-1} in 39 kg ha^{-1} increments) were applied in replicated small plots across an irrigated cornfield in central Nebraska in 2007. Soil variables evaluated for MZ delineation included maps of apparent soil electrical conductivity (EC_a), soil optical reflectance, and landscape topography. Crop response to N was determined via active sensor assessments of in-season canopy reflectance (chlorophyll index; CI_{590}) and grain yield measurements. The relationships between soil and crop response variables were evaluated, and selected soil variables were used to delineate MZ. Crop response had the highest correlation to EC_a and relative elevation ($Elev_{rel}$). Economic analysis showed potential benefits to N management using soil-based MZ compared to the current producer N rate for this field. Further economic benefits could potentially be achieved by integrating soil-based MZ and in-season sensor-based N application.

Keywords: Crop canopy sensors, site-specific nitrogen management, precision agriculture, corn

INTRODUCTION

Current nitrogen (N) management practices have contributed to low nitrogen use efficiency (NUE), estimated to be as low as 30-40% for cereal crops such as corn (Raun and Johnson, 1999; Cassman et al., 2002). Contributing factors to low NUE abound, but can ultimately be summarized in 3 main points, as stated by Shanahan et al. (2008): (1) poor synchrony between soil N supply and crop demand, (2) uniform application rates of fertilizer N to spatially variable landscapes, and (3) failure to account for temporally variable influences on crop N need. For NUE to increase above 30-40%, innovative plant- and soil-based N management strategies are needed to address these factors that contribute to low NUE.

Plant-based methods to increase NUE have included use of the SPAD chlorophyll meter. Varvel et al. (1997, 2007) found that "spoon-feeding" N fertilizer based on leaf greenness measurements using a SPAD chlorophyll meter could be used to reduce N applications while maintaining near optimum yields. However, extending this tool and concept to whole-field management is problematic since it is difficult to collect sufficient data using a hand-held device to manage large fields (Schepers et al., 1995). As a more practical alternative to the SPAD chlorophyll meter for use in large scale applications, active crop canopy sensors have been studied as a remote sensing tool to accurately assess in-season plant N status and direct spatially-variable N applications (Solari et al., 2008; Raun et al., 2002). Active canopy sensors generate modulated light in the visible (400-700 nm) and near-infrared (NIR) (700-1000 nm) regions of the electromagnetic spectrum. Solari et al. (2008) found that active canopy sensors were strongly correlated to SPAD measurements, and could be used to assess canopy N content and direct in-season N application. Solari (2006) developed an algorithm to convert active sensor canopy reflectance measurements at two preselected wavelengths into N application rates for corn. However, he also stated that more research was needed to evaluate whether the algorithm could be used in a variety of soil and climatic conditions.

Soil-based methods to increase NUE have included the concept of management zones (MZ). The concept of MZ has been studied extensively for the past 20 years as an alternative to uniform N management. Management zones are defined as sub-regions of a field with homogeneous attributes in landscape and soil conditions resulting in similar regions of yield-limiting factors or yield potential (Doerge, 1999), and consequently with similar input-use efficiency or potential environmental impact. A variety of data layers have been used to delineate MZ within fields. These have included, but are not limited to: soil survey maps (Franzen et al., 2002); topography (Kravchenko and Bullock, 2000); remote sensing and farmer experience (Fleming et al., 2000); apparent soil electrical conductivity (EC_a) (Kitchen et al, 2005); yield maps (Flowers et al., 2005); soil color (Hornung et al., 2006); and soil brightness, elevation, and EC_a (Schepers et al., 2004).

Delineating fields into MZ has produced mixed results, characterizing homogeneous production areas well in some years, but not in others. For example, Schepers et al. (2004) found that MZ based on soil brightness, elevation, and electrical conductivity appropriately characterized spatial yield patterns in three out of five seasons. However, spatial yield patterns changed significantly in the wettest and driest years in their dataset, and did not correspond to the delineated MZ, suggesting that the static soil-based MZ concept alone would not be adequate for variable application of crop inputs like N across temporal variability. They further suggested that the combination of MZ with a crop-based in-season remote sensing system could produce a more efficient method to apply crop inputs such as N. A responsive in-season N application approach combining MZ and crop-based remote sensing was suggested again by Shanahan et al. (2008) as a possible strategy to increase efficiency of crop inputs such as N. Therefore, the objectives of this study were to identify (1) soil variables that might be useful for MZ delineation and (2) determine if MZ could be valuable in identifying field areas with differential crop response to N and hence be effective in guiding spatially variable N applications.

MATERIALS AND METHODS

Research Field and Experimental Treatments

This study was conducted during the 2007 growing season on a strip-tilled, sprinkler irrigated producer cornfield in central Nebraska. The field consisted of 3 soil series: Crete silt loam (Pachic Argiustoll), Hastings silt loam (Udic Argiustoll), and Hastings silty clay loam (Udic Arigiustoll). The silt loams had minimal slope (0 to 1%) while the silty clay loams had slopes (3 to 11%) with moderate topsoil erosion. The research field provided a range of within-field spatial variability in topography and soil conditions to address the study objectives.

The producer planted the field on May 5 using Pioneer 34R67 seeded at 79040 seeds ha^{-1} on 0.76 m row spacing. Nitrogen treatments for this study consisted of 8 rates ranging from 0 to 274 kg ha^{-1} in 39 kg ha^{-1} increments. Plots were arranged in a 3 x 3 randomized complete block design (RCBD) with the 8 N rates randomized around a central check plot (0 kg ha^{-1}) (Fig. 1). The stationary check plot was used to assess the soil's ability to support crop growth, through mineralized N, at equal distances across the landscape (45.6 m apart). Individual plots consisted of eight rows by 15.2 m in length. Sixteen treatment blocks were located end-to-end in the field, traversing the different soil series within the field. These N treatments were applied after seeding as 28% UAN (urea-ammonium-nitrate) solution.

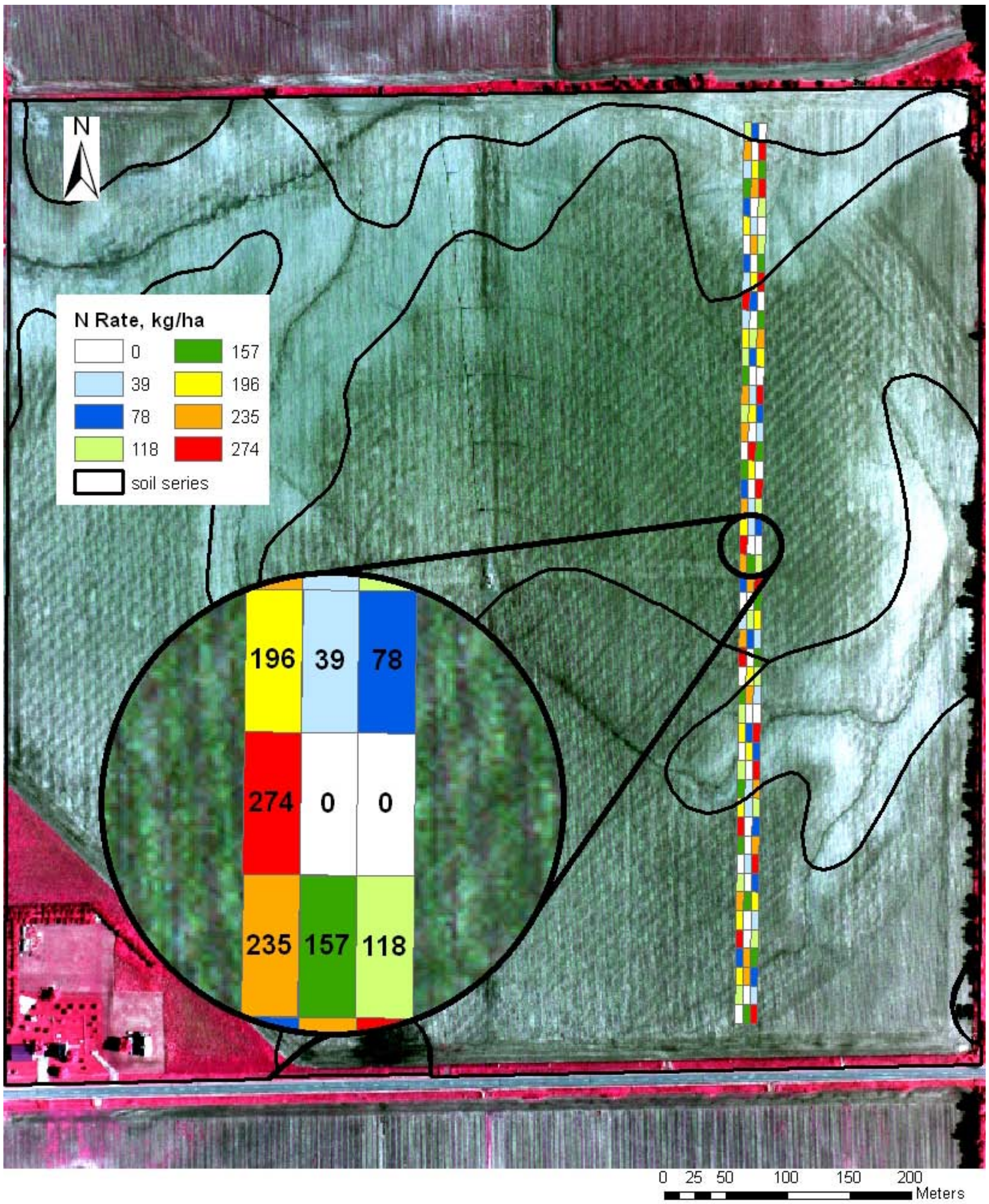

Fig 1. Experimental layout of small plots arranged in randomized complete blocks extending the length of the field. The inset shows one block of treatments.

Soil Data Layers

The spatial data layers collected included soil optical reflectance (visible and NIR reflectance bands from an active sensor), apparent electrical conductivity (EC_a), relative elevation, and slope. All spatial data were georeferenced with a Global Positioning System (GPS) receiver. Spatial coordinates for all data were converted using Universal Transverse Mercator (UTM) Zone 14N (NAD-83 Datum) projection. Spatial data analysis was conducted using ArcMap 9.2 (ESRI, Redlands, CA).

Soil EC_a was mapped prior to planting using a Geonics EM38 (Geonics Ltd, Mississauga, Ontario, Canada). The EM38 instrument provides a measure of ground conductivity and magnetic susceptibility at integrated soil depths of 0 to 0.75 m (horizontal dipole mode; EC_{sh}) and 0 to 1.5 m (vertical dipole mode; EC_{dp}). To collect readings, the EM38 was fastened into a plastic/fiberglass sled pulled behind an all terrain vehicle (ATV). A Trimble AgGPS114 receiver (Trimble Navigation Ltd, Sunnyvale, CA) was mounted next to the sensor to record geographic coordinates as the ATV made parallel passes ~15 m apart from each other through the field.

Soil optical reflectance was assessed at the time of planting using the Holland Scientific ACS-210 Crop Circle active sensor (Holland Scientific, Inc., Lincoln, NE). This sensor generates modulated light in the visible and NIR regions of the electromagnetic spectrum and measures reflectance with visible (590 ± 5.5 nm, VIS_{soil}) and NIR detectors (880 ± 10 nm, NIR_{soil}). To acquire sensor readings, the sensor and data logger were mounted on the front of an ATV ~0.6 m above the soil surface. The sensor was positioned over the soil surface in the nadir view, producing a footprint of approximately 8 by 40 cm, with the long dimension of this footprint oriented parallel to the direction of travel. The sensor footprint was positioned over the planted cornrow to minimize crop residue in the sensor field-of-view as the ATV followed behind the planter. Because soil reflectance is influenced by surface soil moisture content, a distance ~90 m was maintained between the ATV and the planter. This separation distance between the planter and ATV resulted in data collection < 1 min. after soil disturbance, providing a moderate amount of soil water content and soil color differentiation at the time of data collection. The distance between consecutive ATV passes across the field was equal to the planter width (24 rows). A Garmin 18 (Garmin International, Inc., Olathe, KS) GPS receiver with an update rate of 5 Hz was mounted next to the sensor. Sensor readings were collected at 10 Hz while the ATV traveled ~10 km hr^{-1}, resulting in ~0.56 m between consecutive data points. Linear interpolation was applied to assign unique geographic coordinates to each recorded measurement.

Elevation data was also recorded at the same time as collection of soil optical reflectance readings. The Garmin 18 receiver had claimed horizontal accuracy below 3 m. Although this did not provide a high level of elevation accuracy, general elevation trends were observed. Relative elevation ($Elev_{rel}$) was calculated by subtracting the minimum elevation within the field from all elevation data points. Slope was calculated from elevation data using the spatial analysis tool in ArcMap 9.2.

To obtain values of each soil layer for each small plot, inverse-distance weighting (IDW) was used to provide an interpolated surface for each data layer (VIS_{soil}, NIR_{soil}, simple ratio (SR_{soil}), $Elev_{rel}$, Slope, EC_{dp}, and EC_{sh}) at a spatial resolution of ~0.5 m. To reduce the border effect between plot N applications, data from each soil layer were extracted from a 2-m radius area-of-interest (AOI) around the center of each plot using zonal statistics in ArcMap 9.2. The 2-m radius for each plot was inspected and adjusted slightly if any anomalies could be identified (poor crop stand, pivot tracks, etc.).

Crop Response Data Layers

Canopy Reflectance Sensing

When the crop reached V10 growth stage, canopy reflectance measurements were collected from each plot with the sensor used for soil optical reflectance mapping. To distinguish soil optical reflectance from canopy optical reflectance in this discussion, plant readings will be referred to as VIS_{590} and NIR_{880}. Sensor reflectance in the VIS_{590} and NIR_{880} was used to calculate chlorophyll index (CI_{590}) values according to Gitelson et al. (2005) using the following equation:

$$CI_{590} = \frac{NIR_{880}}{VIS_{590}} - 1 \tag{1}$$

Sensor-based CI_{590} values were used in lieu of the more traditional NDVI because CI_{590} has been found to be more sensitive in assessing canopy N status than NDVI (Solari et al., 2008).

To acquire sensor readings, two sensors were mounted on the front of an eight-row high-clearance vehicle approximately 0.8 to 1.5 m above the crop canopy. The sensors were positioned over rows 2 and 7 in the nadir view. Based on positioning, each sensor produced a footprint of approximately 0.1 by 0.5 m, with the long dimension of this footprint oriented perpendicular to the row direction. This sensor position was determined to be optimal for assessing canopy N status by Solari (2006). Before field operation, each sensor was calibrated by the manufacturer using a proprietary universal 20% reflectance panel with the sensor placed in the nadir position above the panel. The output from each sensor included pseudo-reflectance values for the two parts of the spectrum needed for CI_{590} calculation.

A Garmin 18 GPS receiver with an update rate of 5 Hz was mounted in the center on top of the vehicle cab and offset 3.5 m behind the sensor boom. Canopy reflectance measurements were collected at 10 Hz while the vehicle traveled at a ground speed ~8 km hr^{-1}. Linear interpolation was applied to assign unique geographic coordinates to each recorded measurement. Sensor readings were filtered to exclude soil readings from the crop dataset. This was done by assuming that all data points which fell below average CI_{soil} + 2SD calculated from the soil color dataset were soil measurements, and were removed from the in-season crop sensing dataset. Remaining sensor data points were assumed to be plant measurements. Sensor readings for each plot AOI were extracted using zonal statistics in ArcMap 9.2.

Yield Data

At physiological maturity, two 3-m lengths of adjacent rows (6 m total per plot) were selected for hand-harvest from the center of each plot. Grain samples were oven dried, weighed, and shelled. Grain moisture was measured using a DICKEY-john moisture tester (DICKEY-john Corp., Auburn, IL), and harvested weight was adjusted to a standard moisture of 155 g kg^{-1}.

Yield response to N rate models were fit to each treatment block and used to identify potential outliers in the dataset that required further inspection. Based on previous research by Cerrato and Blackmer (1990) and Scharf et al. (2005), a quadratic-plateau function was used to describe corn yield response to N rate for data of each treatment block using Proc NLIN in SAS 9.1 (SAS Institute Inc., Cary, NC). The stationary check plot within each block was not used in this part of the analysis unless the randomized check plot was not representative of its location in the field (i.e. error in treatment applications, location of pivot track, etc.). Goodness of fit for each model was evaluated according to methods described by Kitchen et al. (2010) and Scharf et al. (2005). Spatial location and yield response models were evaluated for each treatment block, and plots with obvious anomalies were excluded from further analysis.

Data Analysis and Zone Delineation

Pearson correlation analysis was conducted to explore the relationships between the measured soil and crop variables. The crop variables used were Yield, Relative Yield ($Yield_{rel}$), ΔYield, CI_{590}, and partial factor productivity (PFP). $Yield_{rel}$ was calculated within each replication by dividing each yield by the yield obtained from the plot receiving the highest N rate (274 kg ha^{-1}). ΔYield was calculated within each replication by subtracting the check plot (no N applied) yield from yield when N was applied. PFP (kg grain/kg N applied) was used in place of other calculations of NUE because it provides an integrative index that quantifies total economic output relative to utilization of all nutrient resources in the system, including indigenous soil nutrients and nutrients from applied inputs (Cassman et al., 1996). Next, the relationships between check plot yields, CI_{590}, and the different soil variables were explored. This approach was taken to remove the confounding effects of N application on measured variables, and better determine associations between variation in soil attributes and variation in crop response variables. The two soil variables with the highest significant correlation to both check plot yields and CI_{590} were used as input variables for clustering in Management Zone Analyst 1.0.1 (USDA-ARS and University of Missouri, Columbia, MO) (Fridgen et al., 2004). Once soil variables were selected, all plots were input into MZA for classification. Additionally, to increase the total number of points for clustering, and to increase the overall spatial area for clustering, data points located in an adjacent N study were also used as inputs into MZA. Software default values were used for both the measure of similarity (Euclidean distance) and the fuzziness exponent (1.30). The Normalized Classification Entropy (NCE) and Fuzziness Performance Index (FPI) were calculated by MZA as post classification analysis to determine the appropriate number of zones within each field. The optimum number of classes is when both NCE and FPI are minimized, representing the least membership sharing (FPI) or greatest amount of organization (NCE) from the clustering process (Fridgen et al., 2004).

Zone Validation

After clustering in MZA, zones were evaluated to determine whether classification based on soil variables was related to differences in in-season CI_{590} and yield response to N rate. Because canopy reflectance (expressed as CI_{590}) and yield response to N rate are inputs to the current in-season active canopy sensor algorithm developed at the University of Nebraska (Solari, 2006), these two variables were used to test zonal differences in the field.

To evaluate zone delineation using CI_{590} and yield response to N rate, treatment blocks within each field were disregarded and plots were grouped according to N rate within each zone. Although the number of plots for each N rate varied within each zone, plot CI_{590} and yield values were averaged for each N rate within each zone. This resulted in 8 total data points within a zone for both CI_{590} and yield, to which quadratic-plateau models were fit. An F-test was performed to determine whether the models for CI_{590} and yield response to N rate for each zone were statistically different.

Parameters b and c from the quadratic-plateau models were used to calculate the economic optimal N rate (EONR) for each zone. EONR was determined based on a fertilizer to grain ratio of 7, where corn grain price was \$0.158 kg^{-1} (\$4 bu^{-1}) and N fertilizer cost was \$1.10 kg^{-1} (\$0.50 lb^{-1}). EONR was calculated based on the equation:

$$EONR = [b - (\$1.10/\$0.158)]/2c \qquad (2)$$

where b and c were the linear and quadratic coefficients of the quadratic-plateau response function, and where $b > 0$ and $c < 0$ (Scharf et al., 2005). EONR was constrained to never exceed 274 kg N ha^{-1}, the highest N application rate.

RESULTS AND DISCUSSION

Selection of Soil Variables for MZA

To determine soil variables that might be useful for delineating field variability into MZ and if MZ could in turn be useful in identifying field areas with differential crop response to N, the relationships between the soil variables and crop response variables (CI_{590} and Yield) for the 0-N check plots were first explored. Because the current active sensor algorithm incorporates yield response to N and in-season CI_{590} measurements (Solari, 2006), soil-based MZ would need to identify both in-season spatial patterns in canopy reflectance (CI_{590}) and end of season patterns in crop yield. This strategy was taken to remove the confounding effect N application has on the soil-plant system. This strategy appeared to be a useful method to explore how the soil variables can influence the crop in-season and at the end of the growing season (Table 1).

Table 1. Correlation of soil variables to check plot yield and in-season CI_{590}.

Crop Parameter	VIS_{soil}	NIR_{soil}	SR_{soil}	EC_{dp}	EC_{sh}	$Elev_{rel}$	Slope
CI_{590}	-.77***	-.74***	.76***	-.70***	**-.76*** **	**.75*** **	-.26
Yield	-.63***	-.63***	.58***	-.74***	**-.74*** **	**.65*** **	-.52**

**Statistical significance at $P < 0.01$

***Statistical significance at $P < 0.001$

The two variables with the highest significant correlation to CI_{590} and Yield were selected for use in MZA clustering. This analysis indicated that EC_{sh} showed the strongest correlation to both CI_{590} and Yield. It should also be noted in this analysis there was strong correlation between $Elev_{rel}$ and CI_{590} as well as Yield. The strong positive correlation is related to the silt loam content of the soil. Higher positions in the landscape for this field corresponded to higher OM and more productive soils while lower areas in the landscape corresponded to drainage ways. These landscape positions translated to optimal growing conditions in higher elevation areas of this field, resulting in low in-season crop stress and high yields. On the other hand, drainage ways could potentially have higher crop stress during the growing season due to denitrification, leading to lower crop yields.

Management Zone Delineation

Results from MZA were initially evaluated using the two indices (FPI and NCE) calculated by MZA, as previously described. FPI and NCE indicated that optimal clustering occurred with two MZ in the field (data not shown). A zonal classification map is presented in Fig. 2. Zone 1 consisted of darker, more productive soils while Zone 2 consisted of lighter, less productive areas. The darker Zone 1 areas corresponded to productive upland positions in the landscape. Zone 2 areas were associated with eroded slopes and drainage ways where soil fertility is potentially lower and conditions are not suitable for optimal crop growth in most growing seasons (Table 2).

Management Zone Validation

Chlorophyll Index

After using MZA to conduct zone classification, the next step was to determine if crop response to N rate (sensor determined CI_{590}) was affected by MZ classification. For soil-based MZ to be used in conjunction with in-season active sensor based N management, it is essential for the zones to properly identify areas within a field of different levels of N stress. In past research, CI_{590} has been shown to be a good measure of in-season crop N status (Solari et al., 2008), and was therefore used for zone validation.

Fig. 2. Zones 1 and 2 resulting from MZA clustering of soil variables. Data points and soil series are overlaid on a bare soil CIR image.

Table 2. Soil chemical properties for Zones 1 and 2. Soil samples were collected from the 0 to 20 cm depth prior to planting from a 0.7 ha offset grid within the field. An F-test was used to test statistical difference between MZ.

MZ	n	pH	Bray-P	OM
1	11	5.21**	22.9*	35.5**
2	5	6.07**	60.4*	30.2**

*Statistical significance at P < 0.05
**Statistical significance at P < 0.01

A comparison of zonal CI_{590} values is presented in Fig. 3a. The Zone 1 CI_{590} model was statistically different from the Zone 2 model ($p < 0.05$). Zone 1 was located in higher productivity areas of the field which did not exhibit in-season N stress to the extent of Zone 2 areas. These results indicate that the identification of appropriate soil variables to develop MZ within a field can characterize in-season variability in CI_{590} (i.e. identify different areas of N stress within a field).

Although the identification of different areas of N stress within a field is essential for in-season sensor-based N application, the current University of Nebraska active sensor algorithm evaluates crop N stress using a sufficiency index (SI) calculated as:

$$SI_{590} = \frac{CI_{target}}{CI_{high\ N\ reference}} \tag{3}$$

where CI_{target} is the CI_{590} value of an N stressed area and $CI_{high\ N\ reference}$ is the CI_{590} value of a non-N limiting area. N rate was calculated according to the following parametric equation based on the V11 growth stage algorithm proposed by Solari (2006):

$$N\ Rate = 286 \times \sqrt{1.01 - SI_{590}} \tag{4}$$

When zonal SI_{590} is used instead of zonal CI_{590} values, N stress within a zone is normalized and the difference between zones is minimized (Fig. 3b). Zonal SI_{590} were not statistically different ($p < 0.05$); however, N rates required to achieve high SI_{590} values differed substantially between the two zones. These results indicate that soil-based MZ are able to delineate different areas of N stress within this field. Results also show the current sensor-based algorithm accounts for different areas of N stress by using a normalized crop N stress measurement (SI_{590}) in place of CI_{590}.

Yield

Yield response to N rate was statistically different between Zones 1 and 2 (Fig. 3c). Zone 2 consisted of soils on eroded slopes where yield potential was lower than in other non-eroded areas of the field. EONR differed by 72 kg ha^{-1} between Zones 1 and 2. These results indicate that the soil-based MZ were able to appropriately classify yield response to N rate areas within this field. Integrating these zonal yield response models with an in-season sensor-based system could potentially improve the efficiency of the current University of Nebraska sensor-based algorithm.

Economic Considerations

An economic analysis was performed using the 11.6 ha study area within the field. If the current producer N application rate for this field is used (258 kg ha^{-1}), the area designated as zones 1 and 2 are calculated, and a N fertilizer cost of \$1.10 kg^{-1} is assumed, we can calculate the potential savings or loss resulting from applying zone specific uniform N rates compared to the current producer N

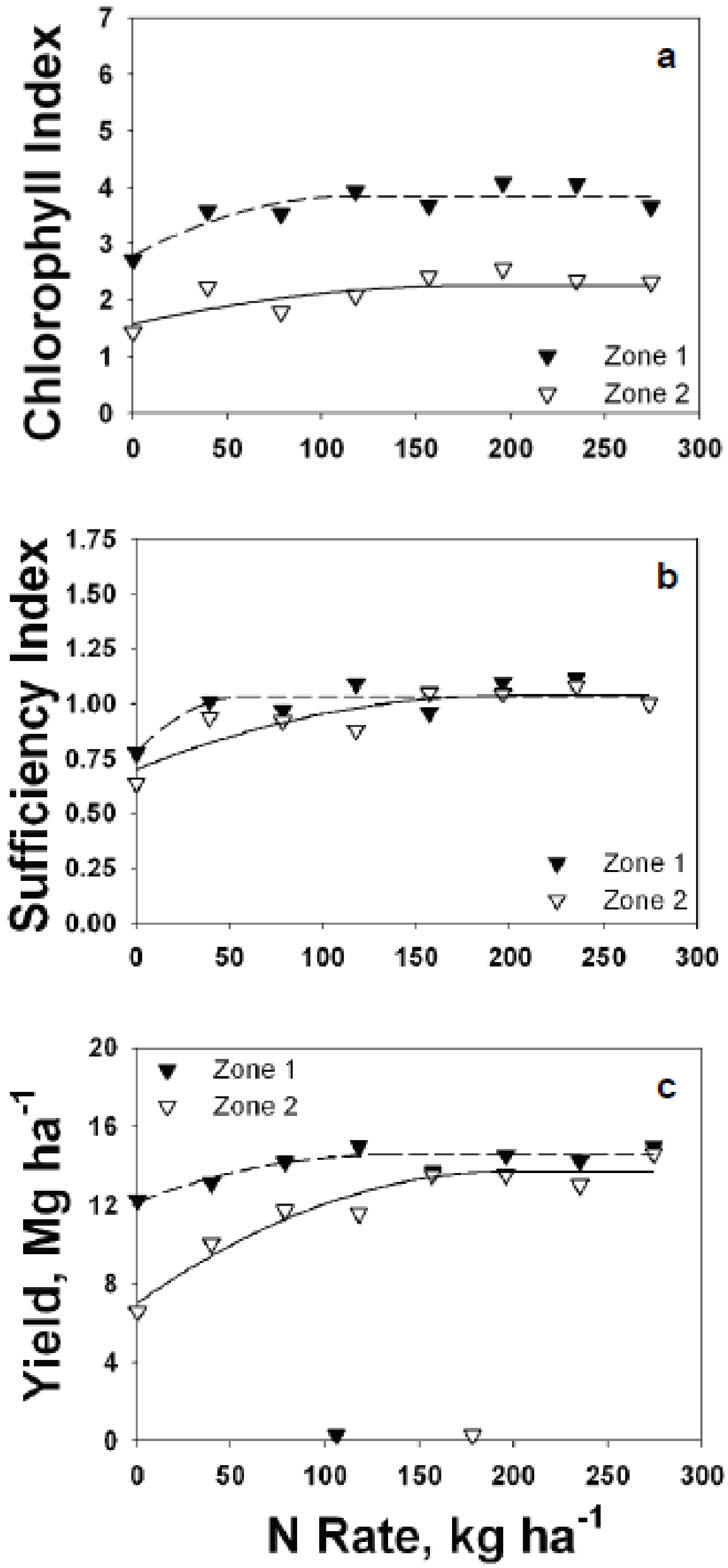

Fig. 3. Crop response to N rate for Zones 1 and 2. Crop response variables included chlorophyll index (a; CI_{590}), sufficiency index (b; SI_{590}), and yield (c). EONR for Zones 1 and 2 is indicated by the corresponding symbol on the x-axis in part c.

application rate. These assumptions result in a total N savings for N application to our study area of \$146 ha^{-1}. Extrapolated to a typical Nebraska pivot area of ~57 ha, the total savings is \$8322. The substantial N savings measured suggests there is potential benefit to N application according to soil-based MZ. The benefit of site-specific management in this field could potentially be increased further through the integration of active canopy sensor-based variable-rate N application adjusted to account for within-field MZ, as suggested by Shanahan et al. (2008) and Scharf et al. (2005). Further research in this area is warranted.

Additionally, results from this study showed that further modifications to the current sensor-based algorithm could potentially increase the N application efficiency. For example, the current active canopy sensor algorithm is based on maximum yield being attained at ~180 kg N ha^{-1} in-season (Solari, 2006). Results showed that N rate at maximum yield differed between zones by 68 kg ha^{-1}. As an initial algorithm modification, N rate at which maximum yield is attained could potentially be changed based upon the zonal yield response to N rate measured in this study.

CONCLUSIONS

In this study it was found that soil properties could be used to delineate within-field MZ that identified spatial variability in crop in-season response to N rate (CI_{590}) and crop yield. In this analysis, MZ delineated using a combination of EC_a and $Elev_{rel}$ identified significantly different areas of CI_{590} and yield response to N rate. An economic analysis showed potential benefit to spatially variable N applications using soil-based MZ compared to field-uniform applied N. Economic benefits were found for this predominantly silt loam field having substantial topographical relief and eroded slopes. Further economic benefits could potentially be achieved by integrating soil-based MZ and in-season sensor-based N application.

REFERENCES

Cassman, K.G., A. Dobermann, and D.T. Walters. 2002. Agroecosystems, nitrogen-use efficiency, and nitrogen management. Ambio. 31:132-140.

Cassman, K.G., G.C. Gines, M.A. Dizon, M.I. Samson, and J.M. Alcantara. 1996. Nitrogen-use efficiency in tropical lowland rice systems: contributions from indigenous and applied nitrogen. Field Crops Res. 47:1-12.

Cerrato, M.E., and A.M. Blackmer. 1990. Comparison of models for describing corn yield response to nitrogen fertilizer. Agron. J. 82:138-143.

Doerge, T. 1999. Management zone concepts. SSMG-2. *In* Clay et al. (ed.) Site specific management guidelines. Available at http://www.ipni.net/ppiweb/ppibase.nsf/$webindex/article=375FAC448525695A00559405CF15E6B8 (verified 20 April 2010). International Plant Nutrition Institute, Norcross, GA.

Fleming, K.L, D.G. Westfall, D.W. Wiens, M.C. Brodahl. 2000. Evaluating farmer defined management zone maps for variable rate fertilizer application. Prec. Ag. 2:201-215.

Flowers, M., R. Weisz, and J.G. White. 2005. Yield-based management zones and grid sampling strategies: describing soil test and nutrient variability. Agron. J. 97:968-982.

Franzen, D.W., D.H. Hopkins, M.D. Sweeney, M.K. Ulmer, and A.D. Halvorson. 2002. Evaluation of soil survey scale for zone development of site-specific nitrogen management. Agron. J. 94:381-389.

Fridgen, J.J., N.R. Kitchen, K.A. Sudduth, S.T. Drummond, W.J. Wiebold, and C.W. Fraisse. 2004. Management Zone Analyst (MZA): software for subfield management zone delineation. Agron. J. 96:100-108.

Gitelson, A.A., A. Vina, V. Ciganda, D.C. Rundquist, and T.J. Arkebauer. 2005. Remote estimation of canopy chlorophyll content in crops. Geophys. Res. Lett. 32: L08403, doi: 10.1029/2005GL022688.

Hornung, A., R. Khosla, R. Reich, D. Inman, and D.G. Westfall. 2006. Comparison of site-specific management zones: soil-color-based and yield-based. Agron. J. 98:407-415.

Kitchen, N.R., K.A. Sudduth, D.B. Myers, S.T. Drummond, and S.Y. Hong. 2005. Delineating productivity zones on claypan soil fields using apparent soil electrical conductivity. Comput. Electron. Agric. 46:285-308.

Kitchen, N.R., K.A. Sudduth, S.T. Drummond, P.C. Scharf, H.L. Palm, D.F. Roberts, and E.D. Vories. 2010. Ground-based canopy reflectance sensing for variable-rate nitrogen corn fertilization. Agron. J. 102:71-84.

Kravchenko, A.N., and D.G. Bullock. 2000. Correlation of corn and soybean grain yield with topography and soil properties. Agron. J. 92:75-83.

Raun, W.R., and G.V. Johnson. 1999. Improving nitrogen use efficiency for cereal production. Agron. J. 91:357-363.

Raun, W.R., J.B. Solie, G.V. Johnson, M.L. Stone, R.W. Mullen, K.W. Freeman, W.E. Thomason, and E.V. Lukina. 2002. Improving nitrogen use efficiency in cereal grain production with optical sensing and variable rate application. Agron. J. 94:815-820.

Scharf, P.C., N.R. Kitchen, K.A. Sudduth, J.G. Davis, V.C. Hubbard, and J.A. Lory. 2005. Field-scale variability in optimal nitrogen fertilizer rate for corn. Agron. J. 97:452-461.

Schepers, A.R., J.F. Shanahan, M.A. Liebig, J.S. Schepers, S.H. Johnson, and A. Luchiari, Jr. 2004. Appropriateness of management zones for characterizing spatial variability of soil properties and irrigated corn yields across years. Agron. J. 96:195-203.

Schepers, J.S., G.E. Varvel, and D.G. Watts. 1995. Nitrogen and water management strategies to reduce nitrate leaching under irrigated maize. J. Contam. Hydrol. 20:227-239.

Shanahan, J.F., N.R. Kitchen, W.R. Raun, and J.S. Schepers. 2008. Responsive in-season nitrogen management for cereals. Comput. Electron. Agric. 61:51-62.

Solari, F. 2006. Developing a crop based strategy for on-the-go nitrogen management in irrigated cornfields. Ph.D. diss. Univ. of Nebraska, Lincoln.

Solari, F., J. Shanahan, R. Ferguson, J. Schepers, and A. Gitelson. 2008. Active sensor reflectance measurements of corn nitrogen status and yield potential. Agron. J. 100:571-579.

Varvel, G.E., J.S. Schepers, and D.D. Francis. 1997. Ability for in-season correction of nitrogen deficiency in corn using chlorophyll meters. Soil Sci. Soc. Am. J. 61:1233-1239.

Varvel, G.E., W.W. Wilhelm, J.F. Shanahan, and J.S. Schepers. 2007. An algorithm for corn nitrogen recommendations using a chlorophyll meter based sufficiency index. Agron. J. 99:701-709.