Relationships between Soil-Based Management Zones and Canopy Sensing for Corn Nitrogen Management

Darrin F. Roberts,* Richard B. Ferguson, Newell R. Kitchen, Viacheslav I. Adamchuk, and John F. Shanahan

ABSTRACT

Integrating soil-based management zones (MZ) with crop-based active canopy sensors to direct spatially variable N applications has been proposed for improving N fertilizer management of corn (*Zea mays* L.). Analyses are needed to evaluate relationships between canopy sensing and soil-based MZ and their combined potential to improve N management. The objectives of this study were to: (i) identify soil variables related to in-season crop canopy reflectance and yield and use these variables to delineate MZ for N fertilizer management; and (ii) compare corn yield response to different N fertilizer treatments for different MZ. Eight N rates (0–274 kg N ha^{-1} in 39 kg ha^{-1} increments) were applied in replicated small plots across six irrigated fields in 2007 to 2008 throughout central Nebraska. Soil variables evaluated for MZ delineation included: 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. Relationships between soil and topography data and crop performance were evaluated, with selected soil variables used to delineate two MZ within four of the six fields. Economic benefits to N application according to soil-based MZ were observed in fields with silty clay loam and silt loam soils with substantial relief and eroded slopes. Sensor-based algorithms may need to be adjusted according to MZ to account for differences in crop N response.

Nitrogen management in cereal crops has been the subject of considerable research and debate for several decades. Inefficient N management practices have contributed to low (~30–40%) N use efficiency (NUE) estimates 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 three main points, as stated by Shanahan et al. (2008): (i) poor synchrony between soil N supply and crop demand; (ii) uniform application rates of fertilizer N to spatially variable landscapes; and (iii) failure to account for temporally variable influences on crop N needs. Poor synchronization between soil N supply and crop demand is the result of N application before crop establishment and failure to account for N mineralization, leaving inorganic N in the soil subject to denitrification, leaching, or volatilization. Previous studies have found that in-season N application resulted in higher NUE than preplant applied N (Welch et al., 1971; Randall et al., 2003a,b). Studies have also shown that optimal N rates vary spatially across a field (Mamo et al., 2003; Scharf et al., 2005; Shahandeh et al., 2005) and using tools to account for this variability could potentially increase NUE (Hong et al., 2007). Therefore, innovative N management strategies are needed to address the factors that cause relatively low NUE.

Soil-based methods to increase NUE have included the concept of management zones (MZ). Management zones are defined as subregions of a field with relatively homogeneous attributes in landscape and soil conditions, resulting in similar yield-limiting factors or yield potential (Doerge, 1999). Implied is that these MZ would have similar input-use efficiencies. Delineating MZ has included mathematical assessment of quantitative data sets to determine groups or clusters of data that are most similar. Methods for performing this data clustering to create MZ have varied considerably, with no universal algorithm being widely accepted. As reviewed by Fridgen et al. (2004), methods include supervised clustering, unsupervised clustering, *c*-means (*k*-means), fuzzy *c*-means (fuzzy *k*-means), and others. Management Zone Analyst (MZA, USDA-ARS Cropping Systems and Water Quality Research Unit, Columbia, MO) is a software program developed using Microsoft Visual Basic (Microsoft Corp., Redmond, WA) that uses a fuzzy *c*-means algorithm. The advantage of MZA over other software programs is that it provides concurrent output for a range of cluster numbers, so the user can define the optimum number of MZ (Fridgen et al., 2004).

A variety of data types have been used to delineate MZ within fields. These have included, but are not limited to: soil survey maps (Franzen et al., 2002); modified soil survey maps (Carr et al., 1991); topography (Kravchenko and Bullock, 2000); remote sensing and farmer experience (Fleming et al., 2000); EC$_a$ (Fraisse et al., 2001; Kitchen et al., 2005); EC$_a$, grain yield, or slope and texture (Ferguson et al., 2003); yield

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Published in Agron. J. 104:119–129 (2012)
Posted online 1 Dec 2011
doi:10.2134/agronj2011.0044

Abbreviations: CI, chlorophyll index; EC$_a$, apparent electrical conductivity; EONR, economically optimal nitrogen rate; FPI, fuzziness performance index; MZ, management zones; NCE, normalized classification entropy; NDVI, normalized difference vegetation index; NIR, near infrared; NUE, nitrogen use efficiency; OM, organic matter; VIS, visible.

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 EC_a appropriately characterized spatial yield patterns in three out of five seasons. The spatial yield patterns changed significantly in the wettest and driest years, however, and did not correspond to the delineated MZ. Due to temporal variability, they concluded that the static soil-based MZ concept alone would not be adequate for variable application of crop inputs like N fertilizers.

One plant-based method that has been used to increase NUE has involved the indirect measurement of crop N status with the SPAD chlorophyll meter (Konica Minolta Sensing, Ramsey, NJ). 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. Extending this tool and concept to whole-field management is problematic, however, because it is difficult to collect sufficient data using a hand-held device to manage large fields (Schepers et al., 1995). Ground-based active crop canopy sensors have been studied as a more practical alternative to the SPAD chlorophyll meter in large-scale assessments of in-season plant N status and to direct spatially variable N applications (Raun et al., 2002; Solari et al., 2008). 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. More recently, Solari et al. (2010) developed an algorithm to convert active sensor canopy reflectance measurements at two preselected wavelengths into N application rates for corn. Using a sufficiency index (SI), a site-specific N application rate (N_{app}) was determined according to

$$N_{app} = 317\sqrt{0.97 - SI_{sensor}} \qquad [1]$$

where SI_{sensor} is the ratio of reflectance measurements from N-stressed to N-sufficient areas. From long-term wheat (*Triticum aestivum* L.) and corn experiments, Raun et al. (2010) determined yield potential to be independent of the crop N response and suggested that sensor-derived estimates of both should be used to calculate realistic in-season N rates. Dellinger et al. (2008) found the green normalized difference vegetation index (GNDVI) to be strongly related to the economically optimum N rate (EONR) and concluded that GNDVI determined via canopy sensing could potentially be useful to guide sidedress N recommendations. Schmidt et al. (2009) compared GNDVI obtained by canopy sensing with SPAD measurements, the presidedress NO_3 test, and late-season stalk NO_3 test and found that GNDVI was as good an indicator of the EONR as the more conventional tests. Schmidt et al. (2009) further suggested that the ability of canopy sensors to capture spatial and temporal variability in N need makes this technology an attractive alternative to improve NUE in corn production.

Although these results show promise for using canopy sensors to guide in-season N management, these methods only incorporate crop-based measurements. Active sensor soil measurements could potentially help to develop or fine-tune MZ delineation and be used in conjunction with on-the-go crop sensing. Ground-based proximal soil sensing has been shown to predict soil properties correlated with crop productivity (Johnson et al., 2001; Roberts et al., 2011). Schepers et al. (2004), as well as others (Holland and Schepers, 2010; Shanahan et al., 2008; Solari et al., 2008), suggested that the combination of MZ and in-season crop-canopy sensing could produce a more efficient method to optimize N application rates. Shanahan et al. (2008) outlined an integrated soil and crop sensing approach by which soil-based MZ could be used to help adjust sensor-guided N rates. Similarly, Holland and Schepers (2010) provided a sensor-based N application algorithm that incorporated a geospatial MZ scalar to adjust N recommendations for such things as soil sample information. Although previous work suggested the use of an N management approach integrating soil-based MZ and canopy sensing measurements, few if any have explored how this could be done. Therefore, this study was conducted to assess these reflectance by MZ concepts for improving N management on crop production fields. Our specific objectives were: (i) to identify soil variables related to in-season crop canopy reflectance and yield and to use these variables to delineate MZ for N fertilizer management; and (ii) to compare the corn yield response to different N fertilizer treatments for different MZ.

MATERIALS AND METHODS

Research Fields

This study was conducted on six producer fields under sprinkler-irrigated conditions during the 2007 (Fields 1, 2, and 3) and 2008 (Fields 4, 5, and 6) growing seasons (Table 1). All six fields were located in central Nebraska within 100 km of each other and each field included between two and four soil series. Fields 1, 3, and 6 were relatively flat (<3 m of relief), while Fields 2, 4, and 5 had substantial changes in elevation (~8–10 m). The fields were grouped into four broad classifications based on soil texture and topography: silt loam fields with level topography (Fields 3 and 6), silt loam fields with rolling topography and eroded slopes (Fields 2 and 5), sandy fields with level topography (Field 1), and sandy fields with rolling topography and eroded slopes (Field 4). Collectively, the selected fields provided an array of topographic and soil conditions and exhibited a range of within-field spatial variability to address the study objectives.

Experimental Treatments

Tillage practices and crop rotations implemented by the grower at each field were typical for central Nebraska corn production, with hybrid selection, planting date, seeding rate, and other field operations managed by individual producers (Table 2). Nitrogen treatments for this study consisted of eight rates (0–274 kg N ha^{-1} in 39 kg ha^{-1} increments) arranged in a randomized complete block design. Individual plots consisted of eight rows (0.76- or 0.91-m row spacing; Table 2) of 15.2-m length. Blocks were located end-to-end in the field, with the number of blocks per field varying from six to 16 (Table 2) depending on individual field lengths. These N treatments were applied after seeding as either 28 or 32% urea-ammonium nitrate solution.

Table 1. Soil series and soil classification for 2007 and 2008 fields.

Field	Soil series	Soil classification
1	Ipage loamy fine sand	mixed, mesic Oxyaquic Ustipsamment, 0–3% slope
	Thurman loamy fine sand	sandy, mixed, mesic Udorthentic Haplustoll, 0–2% slope
	Thurman loamy fine sand	sandy, mixed, mesic Udorthentic Haplustoll, 2–6% slope
	Novina sandy loam	coarse-loamy, mixed, superactive, mesic Fluvaquentic Haplustoll, 0–2% slope
2	Crete silt loam	fine, smectitic, mesic Pachic Udertic Argiustoll, 0–1% slope
	Hastings silt loam	fine, smectitic, mesic Udic Argiustoll, 0–1% slope
	Hastings silty clay loam	fine, smectitic, mesic Udic Argiustoll, 3–7% slope, eroded
	Hastings silty clay loam	fine, smectitic, mesic Udic Argiustoll, 7–11% slope, eroded
3	Hall silt loam	fine-silty, mixed, superactive, mesic Pachic Argiustoll, 0–1% slope
	Hord silt loam	fine-silty, mixed, superactive, mesic Cumulic Haplustoll, 0–1% slope
4	Thurman loamy fine sand	sandy, mixed, mesic Udorthentic Haplustoll, 2–6% slope
	Valentine fine sand	mixed, mesic Typic Ustipsamment, 9–24% slope
5	Hastings silt loam	fine, smectitic, mesic Udic Argiustoll, 0–1% slope
	Hastings silty clay loam	fine, smectitic, mesic Udic Argiustoll, 3–7% slope, eroded
	Hastings silty clay loam	fine, smectitic, mesic Udic Argiustoll, 7–11% slope, eroded
6	Detroit silt loam	fine, smectitic, mesic Pachic Argiustoll, 0–1% slope
	Wood River silt loam	fine, smectitic, mesic Typic Natrustoll, 1–3% slope

Spatial Soil Measurements

Spatial soil measurements collected for each field included EC_a, soil reflectance, relative elevation, and slope. All spatial data were georeferenced with a differentially corrected global positioning system (DGPS) 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).

To characterize the field variation in soil chemical properties, grid soil samples were collected from each field before corn planting. In the 2007 fields (Fields 1, 2, and 3), grid samples were collected on a 0.7-ha-scale offset grid, and in 2008 fields (Fields 4, 5, and 6), on a 0.4-ha-scale offset grid. Soil samples were collected from the 0- to 20-cm depth using a manual soil probe and analyzed for pH, Bray-P, NO_3^-–N, NH_4^+–N, and organic matter (OM). Additionally, a deep core sample (0–91 cm) was collected from each grid location, divided into 30-cm increments, and analyzed for NO_3^-–N and NH_4^+–N.

Soil EC_a was mapped for each field before planting using a Geonics EM-38 instrument (Geonics Ltd., Mississauga, ON, Canada). The instrument provides a measure of EC_a 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}). The EM-38 was calibrated according to the manufacturer's specifications before data collection in each field. To collect measurements, the EM-38 was fastened into a plastic and fiberglass cart pulled behind an all-terrain vehicle (ATV). A Trimble AgGPS 114 receiver (Trimble Navigation Ltd., Sunnyvale, CA) was mounted next to the sensor to log geographic coordinates as the ATV made parallel passes ~15 m apart through each field.

Soil optical reflectance was assessed at the time of planting using a Holland Scientific ACS-210 Crop Circle sensor (Holland Scientific, 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 datalogger 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 row to minimize crop residue in the sensor field-of-view as the ATV followed behind the planter. The distance between consecutive ATV passes across the field was equal to the planter width (Table 2). A Garmin 18 (Garmin International, Olathe, KS) global positioning system (GPS) receiver with an update rate of 5 Hz was mounted on the ATV next to the sensor. Sensor readings were collected at 10 Hz while the ATV traveled ~10 km h^{-1}, resulting in ~0.56 m between consecutive

Table 2. Producer management practices for 2007 and 2008 fields.

Field	Tillage†	Previous crop	Planting date	Hybrid	Seeding rate	Row spacing	Planter width	N application date	Form of at-planting N	Producer field N rate	Treatment blocks
					seeds ha^{-1}	m	m			kg ha^{-1}	no.
1	NT	soybean	20 Apr. 2007	Pioneer 33N08	77,805	0.76	9.1	25 May 2007	28–0–0–5	149‡	16
2	ST	corn	11 May 2007	Pioneer 34R67	79,040	0.76	18.2	5 June 2007	28–0–0	258	16
3	RT	corn	5 May 2007	Pioneer 34A16	79,040	0.91	7.3	7 June 2007	28–0–0	160§	8
4	NT	soybean	21 Apr. 2008	Pioneer 34R67	79,040	0.76	9.1	16 May 2008	28–0–0–5	224	6
5	ST	popcorn	1 May 2008	Heartland Hybrids NG6783	79,040	0.76	9.1	20 May 2008	28–0–0	258	8
6	CT	corn	14 May 2008	Pioneer 33D47	79,040	0.91	7.3	11 June 2008	82–0–0	258	8

† NT, no-till; ST, strip tillage; RT, ridge tillage; CT, conventional disk tillage.
‡ Does not include 50 kg ha^{-1} soybean credit or 27 kg ha^{-1} NO_3 water credit.
§ Does not include 47 kg ha^{-1} NO_3 water credit.

data points. Linear interpolation was applied to assign unique geographic coordinates to each recorded measurement.

Elevation data from each field were also recorded at the same time as the collection of soil optical reflectance readings. The Garmin 18 receiver had differential correction capability (DGPS using a wide-area augmentation system) with horizontal accuracy usually at <3 m. General trends in elevation were measured within each field (Schmidt et al., 2003). Relative elevation ($Elev_{rel}$) was calculated for each field by subtracting the minimum elevation within the field from all elevation data points. Slope was calculated for each field from elevation data using the spatial analysis tool in ArcMap 9.2.

For every small plot, inverse-distance weighting interpolation was conducted to provide values for each data layer (EC_{dp}, EC_{sh}, VIS_{soil}, NIR_{soil}, $Elev_{rel}$, and slope) 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 from 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 (e.g., poor crop stand or pivot tracks).

Crop Sensing and Yield

In-Season Crop Canopy Reflectance

When the crop reached the V10 to V14 growth stage, canopy reflectance measurements were obtained from each plot with the ACS-210 Crop Circle sensor. Two (2007) or four (2008) sensors were mounted in the front of an eight-row high-clearance vehicle approximately 0.8 to 1.5 m above the crop canopy. In 2007, the sensors were positioned over Rows 2 and 7 in the nadir view. In 2008, one sensor per row was positioned over Rows 3 to 6 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 by Solari (2006) to be optimal for assessing the canopy N status. Due to inclement weather, in-season sensing could not be collected from Field 6 until 1 to 2 d after tasseling. To minimize the effect of the tassels, sensors were mounted slightly off row center for this field. Before field operations, 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.

A Garmin 18 GPS receiver with an update rate of 5 Hz was mounted in the center on top of the vehicle cab and 3.5 m behind the sensor boom. Canopy reflectance measurements were collected at 10 Hz while the vehicle traveled at a ground speed of ~8 km h^{-1}, resulting in raw data points ~0.22 m apart. Linear interpolation was applied to assign unique geographic coordinates to each recorded measurement. Plot alleyway positions were used as an additional tool to check the position of data points and make adjustments as needed.

To distinguish canopy optical reflectance from soil optical reflectance, plant readings are referred to as VIS_{590} and NIR_{880}. Sensor reflectance in the VIS_{590} and NIR_{880} wavelengths were used to calculate chlorophyll index (CI_{590}) values according to Gitelson et al. (2003b, 2005) using

$$CI_{590} = \frac{NIR_{880}}{VIS_{590}} - 1 \qquad [2]$$

Sensor-based CI_{590} values were used in lieu of the normalized difference vegetation index (NDVI) because CI_{590} has been found to be more sensitive in assessing canopy N status than NDVI (Solari et al., 2008). Previous research has shown NDVI to have a curvilinear relationship with the canopy chlorophyll content, causing NDVI to saturate at high canopy densities, while CI_{590} does not saturate (Vina and Gitelson, 2005). Sensor readings were filtered to exclude soil reflectance (i.e., a poor crop stand) from the crop data set. This was done by assuming that all data points that fell below the average soil chlorophyll index (CI_{soil}) + 2σ calculated from the soil color data set were soil measurements to be removed. The remaining plant measurements for each plot area of interest were extracted using zonal statistics in ArcMap 9.2.

Grain Yield

At physiological maturity, 3 m of the middle two rows of each plot were hand harvested, and the grain was oven dried, weighed, and shelled (Schmidt et al., 2002). Grain moisture was measured using a DICKEY-john GAC II moisture tester (DICKEY-john Corp., Auburn, IL) and 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 data set that required further inspection (data not shown). Based on previous research by Cerrato and Blackmer (1990) and Scharf et al. (2005), a quadratic-plateau function was used to describe the corn yield response to N rate for data of each treatment block within each field using Proc NLIN in SAS 9.1 (SAS Institute, Cary, NC). Questionable N treatment plots were excluded from further analysis when field conditions compromised the crop (e.g., pivot tracks or drainage ways). Parameters (a, b, and c) from the quadratic model

$$\text{Yield} = a(\text{N rate})^2 + b(\text{N rate}) + c \qquad [3]$$

were evaluated similarly to the process used by Scharf et al. (2005). When the linear (b) coefficient of the quadratic-plateau model was negative (i.e., yield decreased with the first increment of N fertilizer), yield was modeled as unresponsive to N (i.e., a flat line equal to the average yield of all plots within the block). When the quadratic (a) coefficient of the best-fitting quadratic model was positive (i.e., the response curve became steeper at higher N rates), a linear function was fit to the data. When the quadratic-plateau model failed to converge or was nonsignificant ($\alpha = 0.05$), the yield was modeled as a linear regression function when $P < 0.05$; otherwise yield was considered unresponsive to N application.

Data Analysis and Management Zone Delineation

Pearson correlation analysis was conducted with all fields combined to explore the relationships among the measured soil, topography, and crop variables. The crop variables used were yield, relative yield ($yield_{rel}$), change in yield with N fertilization (Δyield), CI_{590}, and partial factor productivity (PFP, kg grain kg^{-1} N applied). $Yield_{rel}$ was calculated within each block 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 block by subtracting the check plot (no N applied) yield from yield when N was applied. The PFP was used in place of other calculations of NUE because it provides an integrative index that quantifies the total economic output relative to the utilization of all nutrient resources in the system, including indigenous soil nutrients and nutrients from applied inputs (Cassman et al., 1996, 1998).

The relationships among check plot yields, CI_{590}, and the different soil variables were explored. This approach was taken to determine the associations between variation in soil and topography attributes and variation in crop response variables. Also, previous research related to canopy sensing found check plot yields useful in assessing the crop response to N fertilizer (Mullen et al., 2003). Three types of variables were explored: soil reflectance (VIS_{soil} and NIR_{soil}), soil EC_a (EC_{dp} and EC_{sh}), and landscape topography ($Elev_{rel}$ and slope). By field, the soil variable within each of these types giving both significant ($P \leq 0.05$) and the highest correlation to both check plot yields and CI_{590} was used as the input variables for clustering in the MZA software (Fridgen et al., 2004). Once the soil variables for clustering were identified, the area of interest from each plot within each field was input into MZA for classification. Additionally, values for the selected data layer(s) from areas adjacent to the N response plots were also included to increase the spatial area for clustering within each field to develop MZ. The MZA default values were used for both the measure of similarity (Euclidean distance) and the fuzziness exponent (1.30) when clustering involved one data layer. The Mahalanobis option for the measure of similarity and the default fuzziness exponent (1.30) were used when two or more data layers were input for clustering (Fridgen et al., 2004). Two performance indices were calculated by MZA to determine the appropriate number of zones within each field. The normalized classification entropy (NCE) determined the amount of disorganization created by dividing the data into classes (Lark and Stafford, 1997). The fuzziness performance index (FPI) is a measure of membership sharing (fuzziness) among classes (Odeh et al., 1992). The optimum number of zones was determined when both NCE and FPI were minimized, representing the least membership sharing (FPI) or the greatest amount of organization (NCE) from the clustering process (Fridgen et al., 2004). When NCE and FPI class tests were not alike, the index giving the fewest number of classes was selected.

Management Zone Validation

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. For soil-based MZ to be integrated with in-season canopy sensors, zones would need to identify areas within fields having unique crop N needs (CI_{590}) and response to N application (yield). Also, because canopy reflectance (expressed as CI_{590}) and yield response to N rate are inputs to in-season active canopy sensor algorithms (Solari et al., 2010), these two variables were used to test zonal differences within each field.

To evaluate zone delineation using the CI_{590} 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} values were averaged for each N rate within each zone. This resulted in eight total data points within a zone, to which a quadratic-plateau model was fit using the same procedures outlined above for yield data.

Yield response to N rate by MZ was also examined using the same procedures. Plots within each zone were grouped according to N rates, and plot yields were averaged for each N rate within a zone. This also resulted in eight total yield data points within a zone, to which a quadratic-plateau model was fit. Statistical differences between CI_{590} response models and yield response models between the zones within each field were tested by combining the data for the two zones and refitting a quadratic-plateau model to each combined data set. With the resulting models for Zone 1, Zone 2, and the combined model, an *F* test was performed to determine whether the models for each zone were statistically different:

$$F_{3,\mathrm{df}_{e1}+\mathrm{df}_{e2}} = \frac{(\mathrm{SSE_T} - \mathrm{SSE_1} - \mathrm{SSE_2})/3}{(\mathrm{SSE_1} + \mathrm{SSE_2})/(\mathrm{df}_{e1} + \mathrm{df}_{e2})} \quad [4]$$

where SSE_T, SSE_1, and SSE_2 are the sum of squares from the combined, Zone 1, and Zone 2 models, respectively, and df_{e1} and df_{e2} are the degrees of freedom for the Zone 1 and 2 models, respectively.

Parameters *a* and *b* from the quadratic-plateau models were used to calculate the EONR for CI_{590} and yield response to N rate for each zone within a field. The EONR was determined based on a fertilizer price/grain price ratio of 7, where the corn grain price was US\$0.158 kg^{-1} (US\$4 bu^{-1}) and the N fertilizer cost was US\$1.10 kg^{-1} (US\$0.50 lb^{-1}). The EONR was calculated as

$$\mathrm{EONR} = \frac{(\mathrm{US\$1.10/US\$0.58}) - b}{2a} \quad [5]$$

where *b* and *a* are the linear and quadratic coefficients of the quadratic-plateau response function, and $b > 0$ and $a < 0$ (Scharf et al., 2005). The EONR was constrained to never exceed 274 kg N ha^{-1} (the highest N application rate). Differences between zonal EONRs were evaluated using the *F* test above (Eq. [4]).

RESULTS AND DISCUSSION

Selection of Soil Variables for Creating Management Zones

First, the general relationships between crop and soil or topography variables were tested by combining measurements across all fields (Table 3). Soil and topography variables were significantly correlated to yield, Δyield, and CI_{590} but generally with low correlation. Given this overall low correlation of the combined field measurements, we concluded that the relationship between crop responses and soil properties may be specific for each field and should not be used to represent all fields when creating MZ.

The relationships between soil and crop variables were next examined on a field-by-field basis (CI_{590} and yield) when no N fertilizer was applied (Table 4). We chose these two variables because they showed the greatest promise among the crop variables from the first analysis (Table 3), and they are integral components of a canopy sensor algorithm (Solari et al., 2010). Also, for soil-based MZ to be used in conjunction with in-season active sensor-based N management, zones should identify areas within fields having unique crop N needs (CI_{590}) and response to N (yield). A significant correlation for at least one soil variable was found in four of the six fields. The lack of any significant correlations between soil–topography and crop variables in Fields 3 and 6 could be attributed to the relative uniformity and lack of N response within these fields (data not shown). It was concluded that creating MZ for these two fields was unwarranted and that uniform N application

Table 3. Pearson correlation coefficients of soil variables obtained from visible and near-infrared bare soil reflectance (VIS_{soil} and NIR_{soil}, respectively), soil apparent electrical conductivity in vertical and horizontal dipole modes (EC_{dp} and EC_{sh}, respectively), and landscape data (relative elevation [$Elev_{rel}$] and slope) to factors related to yield response to N application (yield, relative yield [$yield_{rel}$], change in yield with N fertilization [Δyield], chlorophyll index [CI_{590}]†, and partial factor productivity [PFP, kg grain kg^{-1} N applied]) for N rate small plots for six site-years of corn in central Nebraska (*n* = 386).

Soil variable	Yield	$Yield_{rel}$	ΔYield	CI_{590}	PFP
VIS_{soil}	0.16**	0.00	–0.04	–0.33***	–0.04
NIR_{soil}	0.23***	0.00	–0.09	–0.28***	–0.02
EC_{dp}	0.35***	–0.07	–0.29***	0.18***	0.13*
EC_{sh}	0.18***	–0.08	–0.20***	0.12*	0.10
$Elev_{rel}$	0.30***	–0.05	–0.21***	0.08	0.12*
Slope	0.39***	0.00	–0.28***	0.36***	0.08

* Statistically significant at $P < 0.05$.

** Statistically significant at $P < 0.01$.

*** Statistically significant at $P < 0.001$.

† $CI_{590} = (NIR_{880}/VIS_{590}) - 1$, where NIR is near infrared and VIS is visible light reflectance.

was the best N management strategy. Therefore, these two fields were excluded from further MZ evaluation.

From each of the three types of measurements (soil reflectance, soil EC_a, and topography), the variable with the highest significant correlation to CI_{590} and yield was identified for the four remaining fields. Variables identified using this selection criterion are highlighted in Table 4. Generally, optical reflectance of the soil gave the strongest correlation with CI_{590} and yield in the sandy fields (Fields 1 and 4), while EC_{sh} showed the strongest correlation with CI_{590} and yield in the silt loam fields with eroded slopes (Fields 2 and 5). The range of EC_a was the smallest in Fields 1 and 4 (data not shown), contributing to the low correlation of EC_a with CI_{590} and yield for these sandy soils.

The strong negative correlation measured for $Elev_{rel}$ in Field 4 and the strong positive correlation in Field 2 was related to the soil texture and OM content of each of these fields (sandy and silt loam soils, respectively). The higher areas of Field 4 are wind-eroded areas of the field (Pollock et al., 1981). These upland eroded areas had lower soil OM than other areas of the field, which resulted in reduced in-season crop reflectance readings and yield compared with the higher soil OM of lowland field areas, similar to that observed by Schepers et al. (2004). In Field 2, the opposite relationship was observed. Higher positions in the landscape for this field corresponded to higher OM and more productive soils, while lower areas in the landscape corresponded to eroded drainageways. These landscape positions translated to optimal growing conditions in higher elevation areas of the field, resulting in low in-season crop stress and higher yields. We suspected that the drainageways potentially had higher crop stress caused by denitrification. Topographic data were useful in explaining yield variability, but, as previously mentioned by Kravchenko and Bullock (2000), crop response to topography can vary substantially from field to field and year to year.

Given the criteria for choosing which variables to use for MZ development (in bold in Table 4), no consistent trend was found among the four fields in how many and which variables to use (from one to three). Additional similar field studies are needed to establish a consistent set of soil and topography variable(s) within a soil type for MZ delineation.

Management Zone Delineation

Selected soil variables from Table 4 were included in MZ delineation using MZA. Based on FPI, two MZ were found to be the optimal number for three out of the four fields (data not shown). For Field 5, FPI indicated four potential zones. Based on NCE, however, only two MZ were needed for all four fields. Therefore, subsequent analyses used only two MZ for each of the four fields. Table 5 provides the average MZ value for data layers used in MZA clustering for each field.

As shown in an example zone classification map for Field 1 (Fig. 1), in each of the four fields, Zone 1 generally consisted of darker, more productive soils, while Zone 2 consisted of lighter, less productive areas. In the sandy fields (Fields 1 and 4), the darker areas of Zone 1 corresponded to slight depressions in

Table 4. Pearson correlation coefficients of soil variables to check plot yield and in-season chlorophyll index (CI_{590}) for each of the six site-years. Bold data indicate selected variables used in management zone delineation.

Field	Crop parameter	*n*	Soil optical reflectance†		Apparent electrical conductivity‡		Landscape	
			VIS_{soil}	NIR_{soil}	EC_{dp}	EC_{sh}	$Elev_{rel}$§	Slope
1	CI_{590}	27	–0.66***	**-0.67*****	0.51**	0.47*	–0.44*	–0.28
	yield	27	–0.31	**-0.32¶**	0.06	0.08	0.02	–0.24
2	CI_{590}	29	**-0.77*****	–0.74***	–0.70***	**-0.76*****	**0.75*****	–0.26
	yield	29	**-0.63*****	–0.63***	–0.74***	**-0.74*****	**0.65*****	–0.52**
3	CI_{590}	15	0.36	0.37	–0.21	–0.10	–0.49¶	0.49¶
	yield	15	0.42	0.43	–0.28	–0.14	–0.26	0.26
4	CI_{590}	12	**-0.73****	–0.72**	–0.04	0.14	**-0.76****	–0.42
	yield	12	**-0.80****	–0.78**	–0.28	–0.11	**-0.65***	–0.31
5	CI_{590}	14	–0.54*	–0.58*	–0.66*	**-0.70****	0.35	–0.01
	yield	14	–0.25	–0.29	–0.75**	**-0.70****	0.04	0.32
6	CI_{590}	54	0.05	0.06	–0.13	–0.23	0.27*	0.37**
	yield	54	0.54***	0.67***	–0.10	–0.33*	–0.09	0.17

* Statistically significant at $P < 0.05$.

** Statistically significant at $P < 0.01$.

*** Statistically significant at $P < 0.001$.

† VIS_{soil} and NIR_{soil}, visible and near-infrared bare soil reflectance, respectively.

‡ EC_{dp} and EC_{sh}, vertical and horizontal dipole apparent electrical conductivity, respectively.

§ $Elev_{rel}$, relative elevation.

¶ Statistically significant at $P < 0.10$.

the landscape (Fig. 1). These lower areas had higher soil OM content, higher NO_3–N (Table 6, MZ 1), and acted as receiving areas for water and therefore had corresponding higher yields, as supported by previous yield maps (not shown). The darker Zone 1 areas of Fields 2 and 5 corresponded to productive upland positions in the landscape. Zone 2 areas of Fields 2 and 5 were associated with eroded slopes and drainageways where conditions were less suitable for crop growth (Table 6), also supported by previous yield maps. For these two fields, the average soil P concentrations of Zone 2 were approximately double those of Zone 1. The higher soil P in Zone 2 was attributed to P fertilization rates exceeding crop P removal. These results show that soil data obtained from ground-based proximal sensors appropriately delineated MZ of unique soil chemical properties.

Nitrogen Management Zone Validation

Chlorophyll Index

For soil-based MZ to be used in conjunction with in-season active sensor-based N management, zones should identify areas within fields with a unique crop response to in-season N application. First, CI_{590} values were examined because they have been shown to be a good measure of the in-season crop N status (Solari et al., 2008). Validation of zones was evaluated by comparing the CI_{590} of the two MZ of each field as a function of N rate. Within each field, CI_{590} quadratic-plateau response models for the two zones were statistically different ($P < 0.05$; Fig. 2), with CI_{590} estimates for Zone 1 being consistently higher than for Zone 2. Higher estimates represent plants with either greater biomass or greater chlorophyll content (Gitelson et al., 2003a, 2005). Additionally, in three of the four fields, the EONR was higher for Zone 1 than Zone 2 areas of the field, with the greatest difference in EONR occurring in Field 4 (Fig. 2). These results suggest that Zone 1 was able to generate more biomass and provide more N to the crop than Zone 2 at the time of sensing.

Table 5. Average values for data layer(s) used in clustering by Management Zone Analyst for Zones 1 and 2 within each field. An *F* test was used to test statistical difference between management zones (MZ).

Field	MZ	*n*	Data layer used in clustering†			
			VIS_{soil}	NIR_{soil}	EC_{sh}	$Elev_{rel}$
1	1	878		1.37***		
	2	487		1.01***		
2	1	1120	0.67***		50.1***	6.08***
	2	254	0.86***		62.2***	2.98***
4	1	505	0.76***			3.06***
	2	683	0.84***			7.92***
5	1	1018			42.6***	
	2	326			53.8***	

*** Statistically significant at ***P*** < 0.001.

† VIS_{soil} and NIR_{soil}, visible and near-infrared bare soil reflectance, respectively; EC_{sh}, horizontal dipole apparent electrical conductivity; $Elev_{rel}$, relative elevation.

While there are potentially many ways to create MZ for N management, the procedure used here identified appropriate soil variables for creating zones with unique in-season variability in CI_{590} (i.e., identified different areas of N stress within a field). These results were similar to those of Inman et al. (2008), who found that soil-based MZ appropriately characterized different areas of in-season N stress at early corn growth (V8) in four of six site-years. Significant differences between Inman et al. (2008) and this research, however, were the vegetation index selected to quantify in-season N stress (NDVI vs. CI_{590}) and the corn growth stage of in-season sensing (V8 vs. V10–V14). Previous studies have shown that NDVI is sensitive to crop N stress when the leaf area index (LAI) is relatively low but tends to saturate with high LAI (Gitelson et al., 2003b, 2005; Shanahan et al., 2008; Solari et al., 2008). These results show that soil and topography variables appropriately classified different areas of in-season crop N stress at the V10 to V14 growth stages when in-season N application would probably occur for Nebraska growing conditions.

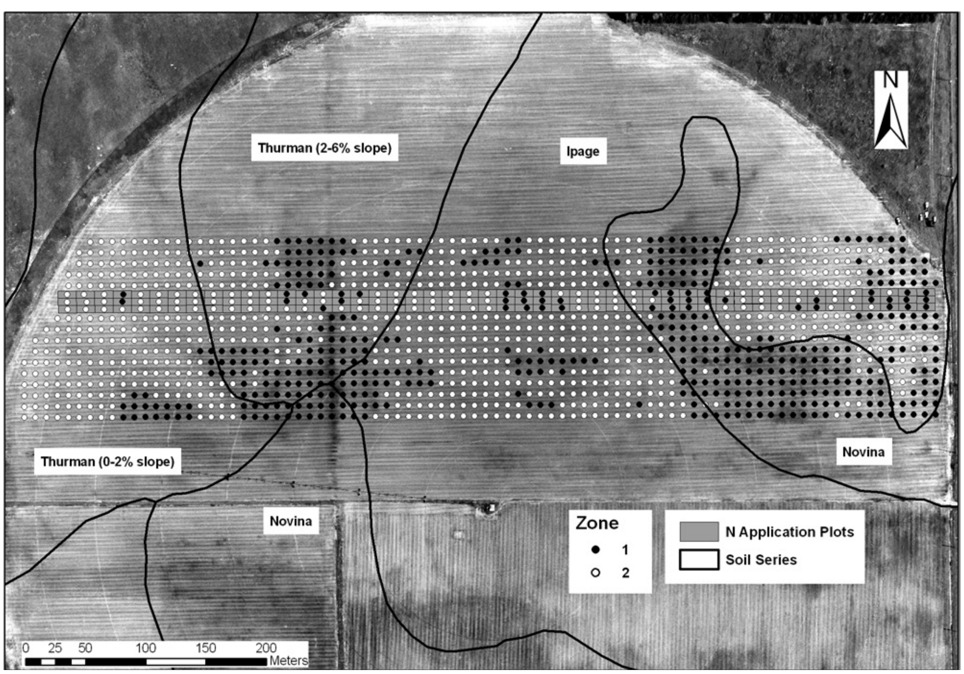

Fig. 1. Zones 1 and 2 for Field 1 resulting from clustering by Management Zone Analyst using near-infrared bare soil reflectance (NIR_{soil}). Zone delineation points, N application plot locations, and soil series are overlaid on a gray-scale bare soil image.

Table 6. Soil chemical properties for management zones (MZ) within each field. Soil samples were collected from the 0- to 20-cm depth. The profile N availability index was calculated as the average soil N (NO_3^-–N + NH_4^+–N) for the top three soil depths (0–91 cm in 30-cm increments). An *F* test was used to test statistical difference between MZ. Statistically different MZ are indicated with the appropriate significance level indicators.

Field	MZ	*n*	pH	Bray-P	Organic matter	NO_3^-–N	NH_4^+–N	Profile N availability index
				mg kg^{-1}	g kg^{-1}	mg kg^{-1}		
1	1	7	7.17	22.8	13.8*	2.04	0.80	3.12
	2	9	7.17	17.0	11.3*	2.12	0.83	2.75
2	1	14	5.34***	30.7†	35.4***	6.18**	1.10*	5.93*
	2	6	6.77***	63.3†	23.4***	3.10**	1.50*	2.27*
4	1	10	6.31	25.6**	25.0*	1.82*	2.89**	4.73**
	2	14	6.43	12.9**	19.4*	1.27*	2.03**	3.70**
5	1	15	6.09**	30.5*	35.0	8.41*	3.52	5.93*
	2	6	6.53**	50.0*	33.3	3.85*	2.00	3.81*

* MZ within a field are statistically significant at $P < 0.05$.

** MZ within a field are statistically significant at $P < 0.01$.

*** MZ within a field are statistically significant at $P < 0.001$.

† MZ within a field are statistically significant at $P < 0.10$.

Grain Yield

The grain yield response to N rate was significantly different between Zones 1 and 2 in Fields 2 and 5 but not in Field 1 ($P < 0.05$; Fig. 3). The maximum yield difference between zones was greatest in Field 5 (2.89 Mg ha^{-1}) and smallest in Field 1 (0.24 Mg ha^{-1}). The lack of a statistically significant quadratic-plateau model for Zone 2 of Field 4 was not surprising because Zone 2 corresponded to wind-eroded areas of the field in the soil survey. These soils have eroded topsoil, lower native soil fertility, and substantial variability in a small spatial area. Therefore, these areas of the field have a lower yield potential than the Zone 1 areas. Also, in-season sensing (CI_{590}) in Field 4 had indicated a substantially lower EONR (44 kg ha^{-1}) in Zone 2 than Zone 1 areas (103 kg ha^{-1}) (Fig. 2); however, smaller experimental block sizes could possibly have better captured the small-scale variability found in Zone 2. In Fields 2 and 5, Zone 2 consisted of soils on eroded slopes where the yield potential was lower than in uneroded areas of the field (Fig. 3). Zonal EONRs of these two fields were different, yet dissimilar between the 2 yr. The Zone 2 EONR for Field 2 was 76 kg ha^{-1} more than that of Zone 1. For Field 5, Zone 2 was 112 kg ha^{-1} less than Zone 1. Because these two fields were similar in soil and landscape properties, we cannot readily explain the dramatic change in EONR for Zone 1 between 2007 and 2008. In general, MZ evaluation based on yield found that more N was needed to reach the EONR in Zone 2 than Zone 1, which supports the idea that Zone 1 will provide more N from the soil, similar to the findings from CI_{590}. Also, the substantially lower zonal EONR predicted using CI_{590} compared with the EONR predicted using yield suggests that crop-based algorithms dependent on CI_{590} may underapply the required N.

These yield results also indicate that soil-based MZ were able to appropriately classify unique zones characterizing yield response to N rate within fields having silt loam soils and eroded slopes. When used in fields with these soil conditions, integrating zonal yield response models or adding a zonal scalar with an in-season sensor-based system could potentially improve the efficiency of sensor-based algorithms, as was proposed by Holland and Schepers (2010).

Economic Considerations

An economic analysis was performed for the four fields, showing potential benefit for using soil-based MZ. The study areas in Fields 1, 2, 4, and 5 were 11.5, 11.6, 10.1, and 11.3 ha, respectively. Using current producer N application rates for each of these fields (Table 2), the areas within each field designated as Zones 1 and 2 were calculated, and the potential savings or loss resulting from applying different N rates to each zone were compared with current producer N application rates. These assumptions resulted in savings for total N application in our study area of –US\$33 ha^{-1}, US\$145 ha^{-1}, US\$0, and US\$32 ha^{-1} for Fields 1, 2, 4, and 5, respectively. Extrapolated to a typical Nebraska pivot area of ~57 ha, the savings or loss would have been –US\$1881, US\$8261, US\$0, and US\$1824 for these fields. Based on the nonsignificant difference between zonal yield responses to N rate models in Field 1, it was not surprising that N application according to MZ resulted in an economic loss for this field. Similarly, the EONR required for the wind-eroded areas of Field 4 (Zone 2, 274 kg ha^{-1}) resulted in no economic benefit for N rates based on MZ compared with uniform N application. The substantial N savings measured in Fields 2 and 5, however, suggests that there is a potential economic benefit to N application according to soil-based MZ in fields with silt loam soils and eroded slopes. These results suggest that the benefit of site-specific management in these fields could 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 Holland and Schepers (2010), Shanahan et al. (2008), and Scharf et al. (2005). Our results indicate that crop-based algorithms would need to be modified to match the unique soil and landscape characteristics of each MZ. For example, the algorithm given by Solari et al. (2010) is based on maximum yield being attained at ~180 kg N ha^{-1} in season. Our results showed that the N rate at maximum yield differed between zones by as much as 114 kg ha^{-1}. As an initial algorithm modification, the N rate at which maximum yield is attained could potentially be adjusted based on the zonal yield response to N rate measured under different soil conditions. Such algorithm modifications would help increase the efficiency of in-season N application compared with uniform N rates. Future studies should include the validation of yield response to in-season N treatment under different soil- and topography-based conditions, which can be delineated using the MZ approach.

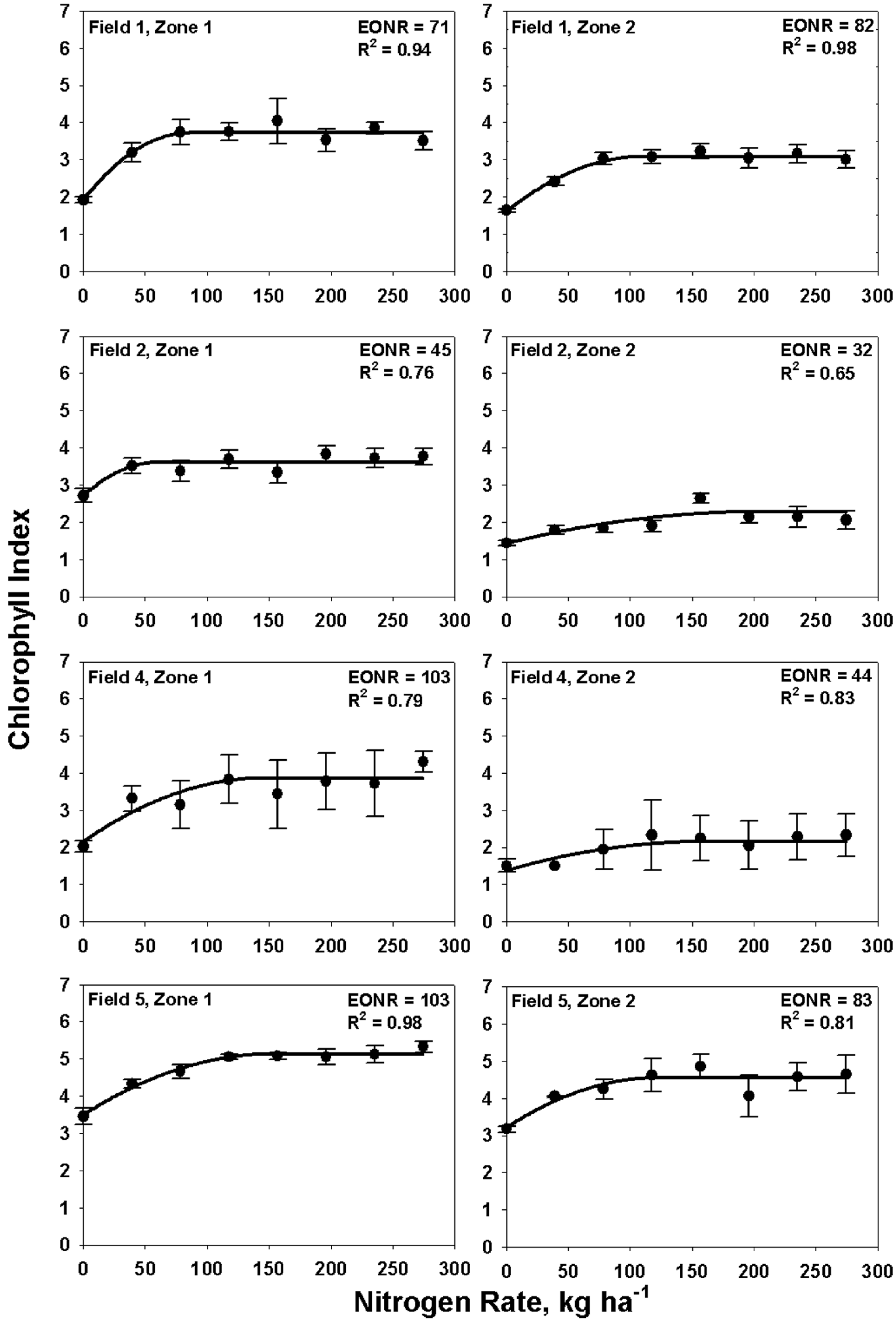

Fig. 2. Chlorophyll index (CI_{590}) response to N rate for Zones 1 and 2 within each field following clustering soil variables in Management Zone Analyst. Quadratic-plateau models were fit to average zone CI_{590} values. The CI_{590} standard error bars are shown for all plots within each zone. Models for Zones 1 and 2 were significantly different within each field ($P < 0.05$).The economically optimum N rate (EONR) was calculated (using SI units) with a fertilizer price/grain price ratio of 7.

CONCLUSIONS

In this study, we found that soil properties could be used under certain soil conditions to delineate MZ within fields that identify spatial variability in the crop in-season response to N rate (CI_{590}) and crop yield. In this analysis, two of six fields were found to have minimal spatial variability in soil properties and no benefit from site-specific N management. In the remaining four fields, check plot CI_{590} values and yields showed the highest correlations with bare-soil reflectance measurements in sandy fields and with EC_a in silt loam fields with eroded slopes. In two of three fields with substantial relief, $Elev_{rel}$ showed a strong correlation with check-plot CI_{590} and yield. When these variables were used to form MZ within each field, different areas of CI_{590} response to N rate were identified in all fields, and different areas of yield response to N rate were identified in three of four fields. These results indicate that, in silt loam fields with eroded slopes, soil-based MZ can identify spatial variability in crop response to N rate and yield. Our results also show that soil data obtained from ground-based proximal sensors can appropriately delineate MZ of unique soil chemical properties.

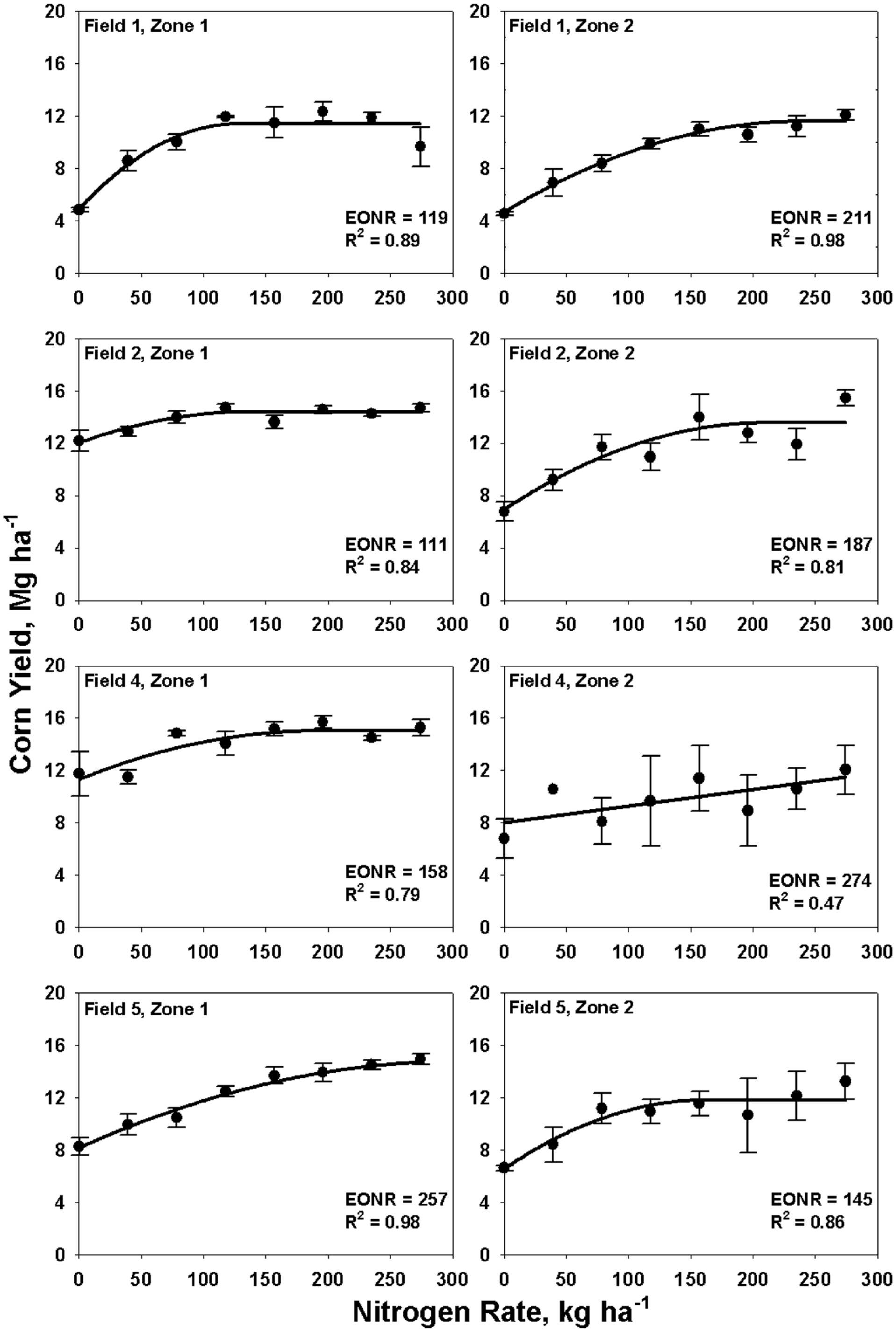

Fig. 3. Yield response to N rate for Zones 1 and 2 within each field following clustering soil variables in Management Zone Analyst. Linear or quadratic-plateau models were fit to average zone yield values (α = 0.05). Yield standard error bars are shown for all plots within each zone. Quadratic-plateau models for Zones 1 and 2 were significantly different within Fields 2 and 5 (P < 0.05). The economically optimum N rate (EONR) was calculated (using SI units) with a fertilizer price/grain price ratio of 7.

A quick economic analysis showed a potential economic benefit to spatially variable N applications using soil-based MZ compared with field-uniform applied N in two of the four fields with delineated MZ. The benefits were observed in fields with silty clay loam and silt loam soils with substantial relief and eroded slopes. Further economic benefits could potentially be achieved by integrating soil-based MZ and in-season sensor-based N application. Sensor-based algorithms may need to be adjusted by zone to account for differences in crop N response.

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