2023

Evaluating management zones and crop-sensing relationships for improved irrigated maize nitrogen management

Joel D. Crowther

John Parrish

Joe Luck

Richard Ferguson

Received: 13 January 2022 | Accepted: 5 August 2022

DOI: 10.1002/agg2.20336

Agrosystems, Geosciences & Environment OPEN ACCESS

ORIGINAL ARTICLE

Agrosystems

Evaluating management zones and crop-sensing relationships for improved irrigated maize nitrogen management

Joel Crowther[1] | **John Parrish**[2] | **Joe D. Luck**[3] | **Richard B. Ferguson**[4]

[1]Land IQ, Sacramento, CA, USA

[2]Sound Agriculture, Emeryville, CA, USA

[3]Department of Biological Systems Engineering, University of Nebraska-Lincoln, Lincoln, NE, USA

[4]Department of Agronomy and Horticulture, University of Nebraska-Lincoln, Lincoln, NE, USA

Correspondence
Joe D. Luck, Department of Biological Systems Engineering, University of Nebraska-Lincoln, Lincoln, NE, USA.
Email: jluck2@unl.edu

Assigned to Associate Editor D. Brian Arnall.

Funding information
National Institute of Food and Agriculture, Grant/Award Number: 2015-67029-23517

Abstract

Active crop canopy sensors and management zones (MZ) are two methods of directing variable-rate, in-season nitrogen (N) fertilizer applications in maize (*Zea mays* L.). Researchers have suggested that integrating these two approaches may result in improved performance of sensor-based N application algorithms through increased N use efficiency and profitability. The objectives of this research study were to (1) identify soil and topographic variables that are related to in-season canopy reflectance and yield for soil-based MZ delineation and (2) determine if delineated MZ can identify areas with differential crop response to N fertilizer. N ramp blocks were placed end-to-end in field-length strips at eight irrigated maize fields in east central Nebraska in 2016 and 2017. Maize response to N was evaluated with in-season canopy reflectance measurements and grain yield. Relationships between maize response variables and measured soil and topographic attributes were evaluated and used to delineate MZ. Yield response to N rate was highly variable among and within fields. Soil apparent electrical conductivity had the highest overall correlations with crop response and was used as a clustering variable in five of eight fields. Economic analysis showed a potential advantage to using soil-based MZ compared to producer-chosen uniform N rates in five of eight fields. Delineated MZ were able to identify areas with differential soil properties and crop response to N fertilizer. Integrating soil-based MZ and sensor-based N management has potential to achieve further economic benefits.

1 | INTRODUCTION

Maize (*Zea mays* L.) is one of the most widely grown crops in the United States and is the largest user of nitrogen (N) fertilizer (Morris et al., 2018). For this reason, fertilizer management under maize production is a target of environmental impact policies where N is concerned (Snyder, 2012). Applied N fertilizer that is not taken up by the crop is subject to numerous loss mechanisms, including denitrification, volatilization, and leaching (Cassman et al., 2002). Fertilizer N use in maize production is historically inefficient, estimates of maize N use efficiency (NUE) ranging from 35% to 75% based on grain recovery (13%–45%) and unrecovered N in the soil–plant system (23%–64%) (Morris et al., 2018). Low NUE has likely contributed to severe environmental consequences in several

Abbreviations: EC_a, apparent electrical conductivity; EONR, economic optimum nitrogen rate; MZ, management zones; NDRE, normalized difference red edge; NIR, near-infrared; NUE, nitrogen use efficiency; RMSE, root mean square error; SI, sufficiency index; SOM, soil organic matter.

regions of the United States including elevated nitrate levels in groundwater across the state of Nebraska (NDEE, 2019).

Three major factors contributing to low NUE in maize production include (1) poor synchrony between soil N supply and crop demand (Shanahan et al., 2008), (2) applying uniform fertilizer N rates to spatially variable landscapes, and (3) failure to account for temporal variability in crop response to N. High levels of inorganic N in the soil profile resulting from large pre-plant N fertilizer applications increases the potential for N loss. In-season N fertilizer applications coincide with the rapid crop uptake period and therefore have great potential to increase NUE (Fageria & Baligar, 2005). Numerous field studies have shown that N supply within a field can be highly spatially variable (Scharf et al., 2005; Shahandeh et al., 2005). This variability is caused by differences in soil organic matter (SOM) mineralization, soil texture, water availability, soil temperature, and local topography. As producers typically apply enough N fertilizer to meet the crop requirements of the most N-limiting field areas, N fertilizer is frequently over-applied, increasing the risk for N loss in field areas requiring less N. Climate and management interactions also result in high temporal variability in the economic optimum nitrogen rate (EONR) and in crop yields (Tremblay et al., 2012). Collectively, these three factors make accurate estimation of EONR difficult for many fields. Innovative N management strategies that can account for these factors are needed to increase NUE and mitigate detrimental environmental impacts.

Delineating fields into management zones (MZs) is one method for managing within-field variability to increase NUE. MZs are sub-field regions (often non-uniform in size or shape) with relatively homogenous soil and landscape attributes, resulting in similar yield-limiting factors and corresponding uniform levels of crop inputs (Doerge, 1999). Myriad approaches to MZ delineation have been developed in the last 25 years (Khosla et al., 2010). Some common attributes that have been used—either individually or in combination—for MZ delineation include soil apparent electrical conductivity (EC_a) (Fleming et al., 2004; Kitchen et al., 1999), yield maps (Flowers et al., 2005), aerial imagery (Schepers et al., 2004), topography (Fraisse et al., 2001), and soil survey maps (D. W. Franzen et al., 2002).

The statistical methods used to classify MZ are diverse. These include the ISODATA method, non-parametric approaches, a hierarchical approach, and the fuzzy *c*-means (or *k*-means) method. Management Zone Analyst (MZA) (University of Missouri, USDA-ARS, Columbia, MO) is a free software program that uses a fuzzy *c*-means algorithm for clustering. In addition to ease of use, MZA has the advantage of providing results for a range of clusters so that the user can evaluate how many MZs should be used (Fridgen et al., 2004).

While managing N through the use of MZ often improves efficiency compared to uniform field management by helping to characterize the spatial variability in soil physical and chemical properties, MZs are often inconsistent in characterizing the spatial variability in crop N requirement because of the effect of temporal variability on crop N response (Shanahan et al., 2008). In a 5-year study in Nebraska, Schepers et al. (2004) found temporal variability to greatly affect MZs, and the use of MZs to direct variable-rate N fertilizer application would have been appropriate in only 3 of 5 years. They concluded that a static, soil-based MZ approach alone is likely inadequate for directing spatially variable applications of N fertilizer due to the inability to account for temporal variability.

One tool with the potential to manage all three factors causing low NUE is crop canopy sensing. This strategy is known as a reactive approach to N fertilizer management because the sensors can identify and correct N stress that has already occurred during the growing season (Ping et al., 2008). Rather than using indirect measures of growing condition from the soil or atmospheric conditions, canopy sensors use the crop itself as a bioindicator to assess crop N status and direct real-time, variable-rate, in-season N fertilizer applications (Adamchuk et al., 2011). Sensor-based N management is able to account for spatial and temporal variability and also helps to achieve greater synchrony between N supply and crop N demand, as the majority of N fertilizer is applied in-season during the period of rapid N uptake. Canopy sensors have been used successfully to direct in-season variable-rate N fertilizer applications in several crops, including maize (Holland & Schepers, 2010), wheat (Solie et al., 2012), cotton (Oliveira et al., 2013), rice (Tubaña et al., 2012), and sugarcane (Amaral et al., 2015).

Crop canopy sensors make use of the relationship between canopy reflectance and crop response to make quantitative in-season N status estimates (Hatfield et al., 2008). Active crop canopy sensors emit modulated light in two or more wavelengths in the visible (400–700 nm) and near-infrared (NIR) (750–1400 nm) regions of the electromagnetic spectrum, and measure the reflectance from the crop canopy with photodetectors. Reflectance in these wavelengths is combined into

Core Ideas

- Soil apparent electrical conductivity had the highest correlations to crop response in five of eight fields.
- Sub-field economic optimum nitrogen rates exceeded 80 kg N h^{-1} for six of eight fields.
- Average economic optimum nitrogen rates ranged from 11 to 96 kg N ha^{-1} between the two management zones (MZs) for six of eight fields.
- Variable-rate nitrogen using soil-based MZs had higher profit potential in five of eight fields.

vegetation indices, which are correlated with chlorophyll content and N sufficiency (Walburg et al., 1982). To assess crop N status, canopy reflectance of plants yet to be fertilized is compared to reflectance from plants receiving an adequate amount of N fertilizer such that N is not a limiting factor (Shanahan et al., 2008). This N-sufficient reference is used to calculate a sufficiency index (SI) (Peterson et al., 1993) (Equation 1):

$$\mathrm{SI} = \frac{\mathrm{VI}_{\mathrm{Target}}}{\mathrm{VI}_{\mathrm{Reference}}}, \tag{1}$$

where

$$0 \leq \mathrm{SI} \leq 1$$

where $\mathrm{VI}_{\mathrm{Target}}$ is the vegetation index of target crop and $\mathrm{VI}_{\mathrm{Reference}}$ is the vegetation index of high-N reference.

Essentially, lower SI values indicate plants with an insufficient N status, which will require more N fertilizer to achieve their yield potential (Shanahan et al., 2008).

Numerous algorithms have been developed to convert sensor reflectance data into an in-season N fertilizer application rate (D. Franzen et al., 2014; Scharf et al., 2011; Solie et al., 2012). Holland and Schepers (2010) developed a generalized N application algorithm for use with crop canopy sensors; they describe the plant growth function as a typical N rate by yield response function (quadratic or quadratic plateau). The algorithm uses an estimated optimum N rate ($\mathrm{N}_{\mathrm{OPT}}$) along with the calculated SI to control the model. This allows economics incorporation into the $\mathrm{N}_{\mathrm{OPT}}$ term and accounts for fertilizer N already applied as well as any N credits.

The use of these systems to direct variable-rate, in-season N fertilizer applications in cereal cropping systems has resulted in positive environmental and economic returns (Kitchen et al., 2010; Roberts et al., 2010). Raun et al. (2002) experimented with sensor-based N application in wheat and found that, averaged over locations, NUE was improved by >15% when compared with traditional uniform practices. The savings in fertilizer N with similar grain yield had a value of >$25 ha^{-1}. Scharf et al. (2011) conducted 55 replicated on-farm experiments in maize comparing sensor-based variable-rate N application to uniform producer-selected rates. Relative to the uniform rate, sensor-based management increased partial profit by $42 ha^{-1}, and applied N was reduced by 16 kg ha^{-1}.

Crop canopy sensors and their corresponding algorithms are not without their limitations. With no direct knowledge of the soil and topographic characteristics underneath the growing crop, the sensor cannot accurately predict how spatial variability may affect future N mineralization or losses that are not expressed in the crop at the time of sensing. This lack of soil-based information has resulted in poor algorithm performance in certain subfield regions due to local spatial variability (R. B. Ferguson, unpublished data, 2015). Researchers agree that refinements are needed in order to account for additional management, soil, and climatic factors (Shanahan et al., 2008), combining both anticipatory and reactive decision-making (Ping et al., 2008). Schepers et al. (2004) and others (Holland & Schepers, 2010; Solari et al., 2008) have suggested that combining MZs and in-season crop canopy sensing may better predict EONR throughout the field and thus achieve greater NUE.

Roberts et al. (2012) experimented with an integrated MZ and canopy sensor approach on six irrigated fields in Nebraska, USA, and found potential for this integrated approach to increase NUE and economic return over current management practices, particularly in silt loam fields with eroded slopes. However, they believed further research was needed to refine current algorithms and explore how to best integrate the two N management strategies. Furthermore, they advocated for additional similar field studies to establish a consistent set of variables for use in MZ delineation. Therefore, the objectives of this research study were to (1) identify soil and topographic variables that are related to in-season canopy reflectance and yield for soil-based MZ delineation and (2) determine if delineated MZs show differential response to N fertilizer.

2 | MATERIALS AND METHODS

2.1 | Research fields

Experiments were conducted on eight center-pivot irrigated maize fields during the 2016 (Fields AR16, CA16, HU16, and KR16) and 2017 (Fields AR17, HU17, JA17, and KR17) growing seasons. Fields were located in east central Nebraska, USA. Fields AR16, KR16, AR17, HU17, and KR17 were relatively flat (<5 m of relief), while there were substantial differences in elevation (~7–20 m) and topography for Fields CA16, HU16, and JA17. The sites were grouped into four classifications based on soil texture and topography: sandy loam, relatively level (KR16 and KR17), silt loam, relatively level (AR16, AR17, HU17), silt loam, eroded slopes (CA16 and HU16), sandy loam, and eroded slopes (JA17). One to four soil series were represented at each site (Table 1).

2.2 | Experimental treatments

Tillage practices, crop rotation, hybrid selection, planting date, seeding rate, irrigation, and other field management decisions and operations were managed by individual producers (Table 2). Each treatment block represented plots arranged as a randomized complete block design which were two plots wide by three plots in length (Figure 3). Plots were 6, 8, or 12 rows (0.76-m row spacing) in width, depending on producer equipment (Table 3). Plot length was 15.2 m with 0.6 m buffers in 2016, and 12.2 m with 3.6 m buffers in

TABLE 1 Field location, soil series, and soil classification for all fields

Field ID	Year	Legal description	Soil series	Soil great group	Slope (%)	SOM range (%)[a]
AR16	2016	T.14N-R.9E, Sec 19, NW ¼, N ½	Filbert silt loam	Vertic Argialbolls	0–1	2.9–5.0
			Tomek silt loam	Pachic Argiudolls	0–2	
			Yutan silty clay loam	Mollic Hapludalfs	2–6, eroded	
CA16	2016	T.9N-R.2E, Sec 19, NW ¼, W ½, S ½	Deroin silty clay loam	Mollic Hapludalfs	6–11, severely eroded	1.9–3.6
			Hastings silty clay loam	Udic Argiustolls	3–7, eroded	
			Deroin silty clay loam	Mollic Hapludalfs	11–30, severely eroded	
HU16	2016	T.9N-R.7 W, Sec 4, SW ¼, E ½	Hastings silt loam	Udic Argiustolls	0–1	1.9–3.8
			Crete silt loam	Udertic Argiustolls	0–1	
			Hastings silty clay loam	Udic Argiustolls	7–11, eroded	
			Hastings silty clay loam	Udic Argiustolls	3–7, eroded	
KR16	2016	T.16N-R.1E, Sec 21, NW ¼, S ½	Brocksburg sandy loam	Pachic Argiustolls	0–2	0.6–1.7
AR17	2017	T.14N-R.9E, Sec 20, SW ¼, W ½	Yutan silty clay loam	Mollic Hapludalfs	2–6, eroded	1.9–4.7
			Filbert silt loam	Vertic Argialbolls	0–1	
			Tomek silt loam	Pachic Argiudolls	0–2	
HU17	2017	T.9N-R.8 W, Sec 1, NE ¼, N ½	Hastings silt loam	Udic Argiustolls	0–1	2.2–4.4
			Hastings silt loam	Udic Argiustolls	1–3	
JA17	2017	T.16N-R.4 W, Sec 7, SE ¼, S ½	Thurman loamy fine sand	Udorthentic Haplustolls	2–6	0.9–3.1
			Loretto-Thurman complex	Udic Argiustolls	1–3	
			Thurman loamy fine sand	Udorthentic Haplustolls	2–6, eroded	
KR17	2017	T.16N-R.1E, Sec 16, SW ¼, S ½	Thurman loamy fine sand	Udorthentic Haplustolls	2–6	0.7–2.0
			Brocksburg sandy loam	Pachic Argiustolls	0–2	

Abbreviation: SOM, soil organic matter.
[a]Twenty-five soil samples per site at 20-cm depth.

TABLE 2 Producer management practices for all fields

Field ID	Tillage	Previous crop	Planting date (MM/DD/YY)	Hybrid	Seeding rate (seeds ha^{-1})	Producer field N rate (kg ha^{-1})	Harvest date (MM/DD/YY)
AR16	NT	Soybean	5/5/16	Pioneer 1197AM	76,600	195	10/15/16
CA16	NT	Maize	5/19/16	Golden Harvest G07B39-311A	74,130	245	10/20/16
HU16	ST	Maize	5/6/16	Pioneer 1105AM	81,540	245	10/11/16
KR16	NT	Soybean	4/24/16	Pioneer 33D53AM	79,070	188	10/15/16
AR17	NT	Soybean	4/25/17	DeKalb 62–98	81,510	202	10/16/17
HU17	ST	Maize	4/25/17	Pioneer 1306WHR	83,030	235	10/18/17
JA17	NT	Soybean	5/5/17	Pioneer 1690	74,100	163	10/17/17
KR17	NT	Soybean	4/23/17	Pioneer 1498	80,560	244	10/17/17

Abbreviations: NT, no-till; ST, strip-till.

TABLE 3 Nitrogen management practices, plot design information, and field characteristics for all fields

	Base N application			In-season N application					
Field ID	Date (MM/DD/YY)	Crop growth stage[a]	Source	Date (MM/DD/YY)	Crop growth stage[†]	Source	Elevation difference (m)	Plot width (m)	Number of treatment blocks
AR16	3/17/16	Pre-plant	Anhydrous ammonia	6/24/16	V9	28% UAN	4.4	6.1	10
CA16	6/6/16	V2	28% UAN	7/19/16	VT	28% UAN	20.0	6.1	13
HU16	6/17/16	V5	28% UAN	7/11/16	V13	28% UAN	8.5	9.1	15
KR16	6/7/16	V5	32% UAN	6/24/16	V10	32% UAN	4.8	6.1	16
AR17	6/1/17	V4	28% UAN	6/23/17	V11	28% UAN	4.0	6.1	12
HU17	6/8/17	V4	28% UAN	7/5/17	V13	28% UAN	5.1	4.6	14
JA17	6/2/17	V3	30% UAN	6/28/17	V11	32% UAN	7.0	6.1	16
KR17	6/2/17	V4	32% UAN	6/29/17	V11	32% UAN	2.9	6.1	16

Abbreviations: UAN, urea-ammonium nitrate solution; VT, tasseling.

[a]Number of collared leaves.

2017. Blocks were placed end-to-end in a field length strip (Figure 3), with the number of blocks per field varying from 10 to 16 (Table 3).

Nitrogen treatments consisted of six rates ranging from 0 to 280 kg ha^{-1} in 56 kg ha^{-1} increments. Field AR16 had 84 kg ha^{-1} N applied before planting, so rates on that site ranged from 84 to 308 kg ha^{-1} in 45 kg ha^{-1} increments. Field JA17 received a pre-emergence N fertilizer application of 39 kg ha^{-1}. Field KR17 received an N application of 23 kg ha^{-1} as ammonium sulfate (21-0-0-24) at the V4 growth stage to correct a sulfur deficiency. A base N fertilizer rate of 56 kg ha^{-1} was applied to all but the check plots between the V2 and V5 growth stages (Table 3). Field JA17 had a decreased base rate of 17 kg ha^{-1} to account for the pre-emergence N application. The remaining N fertilizer was applied between the V9 and VT growth stages (Table 3) with a goal of applications within the V8–V12 stages, prior to the maximum N uptake rate (Ciampitti & Vyn, 2011). The N fertilizer source for all treatments was either 28% or 32% urea ammonium nitrate solution (Table 3). Nitrogen fertilizer was applied with a high-clearance applicator (Hagie DTS 10; Hagie Manufacturing Co., Clarion, IA, USA), and the fertilizer was applied through a straight stream nozzle between each row. Flow rate was controlled with a pulse-width modulation spray rate controller (PinPoint; Capstan Ag Systems, Topeka, KS, USA). Fertilizer application data were collected with a flowmeter at a rate of 1 Hz and were filtered to exclude erroneous data points.

2.3 | Field data collection

2.3.1 | Soil data

Spatial soil data collected for each field included soil (EC_a and soil optical reflectance (red and NIR bands). These attributes were collected for each field prior to planting (except for Field HU17, for which data were collected following harvest) using a Veris MSP3 on-the-go soil sensing platform (Veris Technologies, Inc., Salina, KS, USA). The MSP3 instrument uses two arrays of coulter-electrode pairs to measure soil EC_a at depths of 0–0.3 m as EC_a shallow (EC_s) and 0–0.9 m as EC_a deep (EC_d) simultaneously. An active optical sensor measured soil reflectance at a depth of ∼5 cm as the MSP3 was towed through the field; red (660 nm) and NIR (940 nm) wavelengths were recorded at 1 Hz intervals (Kweon et al., 2013). The simple ratio (SR_{soil}) ($\frac{NIR}{Red}$) was calculated from the reflectance readings. Twenty-five soil samples were collected to a depth of 20 cm across the range of EC_s and reflectance values for the field, and results were used by Veris Technologies to calibrate the optical reflectance readings to estimate SOM. A global navigation satellite system (AG-372, Trimble, Sunnyvale, CA, USA) receiver was mounted on the MSP3 sensor to log geographic coordinates as the instrument made parallel passes ∼18 m apart throughout the field.

Elevation as 2-m Digital Elevation Model (DEM) grids was retrieved for each field from the Nebraska Department of Natural Resources LiDAR Repository (Merrick & Co., 2011). Relative elevation ($Elev_{rel}$) was calculated for each field by subtracting all grids by the minimum elevation within the field. Slope was calculated with the same grid size as the DEMs using the Spatial Analyst package in ArcMap 10.4 (ESRI, Redlands, CA, USA).

All spatial data were projected into the Universal Transverse Mercator Zone 14N (NAD83 Datum) projection. To obtain values of each data layer for each plot, ordinary kriging was used to interpolate each layer (EC_s, EC_d, SR_{soil}, SOM, $Elev_{rel}$, and Slope). Interpolation was conducted using the Geostatistical Analyst package in ArcMap 10.4. Plots were buffered by one row (0.76 m) on each side and by 2 m at each edge to reduce the possibility of any potential buffer effect between plot N applications. As an additional precaution, pivot tracks were buffered by 1 m. Buffered plots measured 11.2 m in length in 2016 and 9.0 m in 2017, with width varying according to plot row width. Data were extracted from this rectangular area of interest (AOI) using zonal statistics or join in ArcMap 10.4.

2.3.2 | Crop response data

Canopy reflectance was measured at the time of the in-season N application (V9 to VT growth stage) for each plot using an OptRx active canopy sensor (Ag Leader Technology, Ames, IA, USA) (Table 3). Researchers have found the normalized difference red edge (NDRE) vegetation index to be a good measure of in-season crop N status (Li et al., 2014). Canopy reflectance in the red-edge (730 nm) and NIR (780 nm) wavelengths was used to calculate the NDRE vegetation index using Equation (2) (Gitelson & Merzlyak, 1994):

$$\mathrm{NDRE} = \frac{R_{\mathrm{NIR}} - R_{\mathrm{RE}}}{R_{\mathrm{NIR}} + R_{\mathrm{RE}}}, \tag{2}$$

where R_{NIR} is the NIR reflectance and R_{RE} is the red-edge reflectance.

The sensor was mounted to the front of the high-clearance applicator approximately 0.3–0.6 m above the crop canopy. The sensor was positioned over either of the center two rows of each plot in the nadir view. Differential GPS location and reflectance data were logged with a GeoSCOUT X data logger (Holland Scientific, Lincoln, NE, USA). Canopy reflectance measurements were collected at a rate of 1 Hz, while the vehicle traveled at a speed of ∼1.5 m sec^{-1} resulting in raw data points ∼1.5 m apart. Sensor readings were extracted for each plot AOI using zonal statistics in ArcMap 10.4. Sensor readings within the plots were buffered in the same manner as the soils and elevation data.

2.3.3 | Yield data

The entirety of the center two rows of each plot was harvested at physiological maturity with a two-row combine. A Gleaner K combine (AGCO Corp., Duluth, GA, USA) was used for 2016 sites, and the 2017 sites were harvested with a Kincaid 8-XP plot combine (Kincaid Equipment Manufacturing, Haven, KS, USA). Both combines were equipped with a HarvestMaster HM800 GrainGage (Juniper Systems, Logan, UT, USA) for measurement of grain weight, moisture, and test weight. Harvested weight was adjusted to a moisture of 155 g kg^{-1}. Yield was further cleaned by adjusting plot area due to pivot tracks, lodging, and poor stand.

We used a quadratic-plateau function employed by Scharf et al. (2005) and Roberts et al. (2012) to fit yield response to N rate models, which were fit to each treatment block using a quadratic-plateau function using the methods developed by Roberts et al. (2012). This function has been found to best describe maize yield response to N in previous research by Cerrato and Blackmer (1990) and Scharf et al. (2005). PROC NLIN in SAS 9.4 (SAS Institute Inc., Cary, NC, USA) was used to compute the quadratic-plateau function for each block. Two parameters, the coefficient of determination (R^2) and root mean square error (RMSE), were calculated for each model and used to evaluate goodness of fit using Equations (3) and (4):

$$R^2 = 1 - \frac{\mathrm{ESS}}{\mathrm{TSS}}, \tag{3}$$

$$\mathrm{RMSE} = \sqrt{\frac{\mathrm{ESS}}{(n-2)}}, \tag{4}$$

where ESS is the model error sum of squares, TSS is the total sum of squares, and n is the number of observations.

Each of the response functions was plotted along with the observations it described and visually inspected for fit. In a few cases, it appeared that the initial NLIN procedure may not have found the best function, so the NLIN procedure was run again with different starting parameters. This resulted in improved fit of the quadratic-plateau function in a few instances. Additionally, one outlier observation was removed from a small number of blocks when negative yield response to N occurred to improve model fit.

Parameters (a, b, and c) from the quadratic model:

$$\text{Yield} = a + b(\text{Applied N}) + c(\text{Applied N})^2 \quad (5)$$

were evaluated using a process described 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. When the quadratic (c) coefficient of the quadratic model was positive, or when PROC NLIN in SAS failed to converge, a linear function was fit to the data, using PROC REG in SAS 9.4. Yield was modeled as a linear function when $p < 0.10$, and the slope of the line was significantly greater than zero. Otherwise, yield was modeled as unresponsive to N. Three unresponsive treatment blocks were excluded from further analysis; thus, 109 total response functions were presented.

Parameters b and c from the quadratic-plateau models were used to calculate EONR for each treatment block. EONR was determined with a maize grain price of \$120.07 Mg^{-1} and N fertilizer cost of \$0.99 kg^{-1}. EONR was calculated based on Equation (6):

$$\text{EONR} = \frac{(\$0.99/\$120.07 - b)}{2c}, \quad (6)$$

where b and c were the linear and quadratic coefficients of the quadratic-plateau function, and $b > 0$ and $c < 0$ (Scharf et al., 2005). EONR was constrained to never exceed the highest N rate for each field.

2.4 | Management zone delineation

To explore relationships between measured soil and crop variables, a Pearson correlation analysis was conducted using PROC CORR in SAS 9.4. The first analysis explored relationships between check plot yield and NDRE for all check plots. A second analysis utilized all but the check plots, which at the time of sensing had received the same rate of N fertilizer. NDRE was the only crop variable used in the second analysis. Yield for all plots was not explored due to the confounding treatment effect of N on the measured variables.

Using Global (all fields combined) and Field-Specific approaches, the two variables with the highest significant positive or negative correlation ($p < 0.05$ and $R > 0.50$) to either NDRE (at either N Rate) or check yield for each field were selected as input variables (Table 5) for clustering in MZA 1.0.1 (USDA-ARS and University of Missouri, Columbia, MO, USA) (Fridgen et al., 2004). To increase the number of observations for clustering and to increase the overall spatial area of the MZ, all soil and landscape data collected from the plots as well as adjacent to them were used as inputs into MZA, resulting in a total area of 12–30 ha. In the software, Mahalanobis distance was selected as the measure of similarity except when variables with identical units were used. In these instances, Euclidean distance was chosen.

Two indices were calculated by MZA to help determine the optimum number of classes. The normalized classification entropy (NCE) quantified the disorganization created by dividing data into classes (Lark & Stafford, 1997). The fuzziness performance index (FPI) was used to determine the amount of membership sharing (fuzziness) among classes (Odeh et al., 1992). Class number was optimized when both NCE and FPI were minimized, meaning a low degree of membership sharing and low disorganization from the clustering process (Fridgen et al., 2004).

2.5 | Management zone validation

Following MZ delineation for each field, zones were evaluated to determine if there were differences between MZ in terms of response to N. For an initial exploration of MZ, differences in four soil chemical properties—pH, Mehlich-III phosphorus (P), SOM, and cation-exchange capacity (CEC)—were tested. To do this, sample points were grouped by MZ, and an F-test was performed to determine if these properties differed between MZ.

Canopy reflectance (expressed as NDRE) is one input in the Holland–Schepers sensor-based N recommendation algorithm (Holland & Schepers, 2010) and consequently was used as one variable to test zonal differences within each field. To accomplish this, treatment blocks were disregarded, and plots were placed into two groups: those that had received no N fertilizer and those that had received a base rate of 56 kg ha^{-1}. Because the remaining N fertilizer was applied simultaneously with canopy reflectance sensing, all non-check plots had received the same amount of N at the time of sensing. NDRE values were averaged within each plot, and an F-test was used to evaluate zonal differences.

In order to evaluate MZ delineation using yield response to N rate, treatment blocks within each field were disregarded, and plots were grouped according to target N rate within each zone. Only plots located in a block that successfully fit

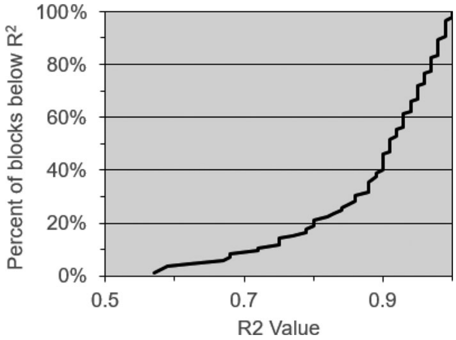

FIGURE 1 Cumulative distribution function for the coefficient of determination (R^2) for all 85 blocks modeled as responsive to N (24 blocks were modeled as unresponsive). About 60% of the models fit the yield data with $R^2 \geq 0.90$.

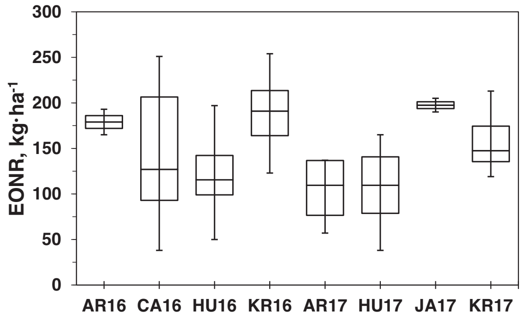

FIGURE 2 Box-and-whiskers plot of economic optimum N rate (EONR) distributions for all eight sites. The upper and lower limits of each box signify the 75th and 25th percentiles for EONR, the horizontal line in the center of the box indicates the median, and the whiskers represent the full range of EONR observed.

a quadratic-plateau function were used. Plot yields and as-applied N fertilizer rates were averaged for each target N rate within each zone. A quadratic-plateau model with six observations was fitted using procedures identical to those outlined previously. Statistical differences between the two models for each field were tested by combining the data for the two zones and re-fitting a quadratic-plateau model to the combined data set (Roberts et al., 2012). With the resulting models for Zone 1, Zone 2, and the combined model, a Chow F-test was performed to determine whether the models for each zone were statistically different (Chow, 1960):

$$F_{k,n_1+n_2-2k} = \frac{\left[\mathrm{SSE_C} - \left(\mathrm{SSE_1} + \mathrm{SSE_2}\right)\right]/k}{\left(\mathrm{SSE_1} + \mathrm{SSE_2}\right)/\left(n_1 + n_2 - 2k\right)}, \tag{7}$$

where $\mathrm{SSE_C}$, $\mathrm{SSE_1}$, and $\mathrm{SSE_2}$ are equal to the residual sum of squares from the combined, Zone 1, and Zone 2 models, respectively; n_1 and n_2 are the number of observations in Zone 1 and Zone 2, respectively; and k is equal to the total number of model parameters.

3 | RESULTS

3.1 | Yield response to nitrogen

The average yield at EONR for all eight sites was 14.2 Mg ha^{-1}, indicating favorable growing conditions and production practices for these experiments (Table 3). Out of 109 total blocks, yield response to N was described using a quadratic-plateau function in 62 blocks, a linear function in 23 blocks, and a nonresponsive function in 24 blocks. The average R^2 for the 85 responsive blocks was 0.88, and median R^2 was 0.91. Sixty percent of all responsive functions had $R^2 \geq 0.90$ (Figure 1).

EONR varied greatly both among and within the eight fields in this study. Median EONR ranged from to 110 to 198 kg ha^{-1} among fields (Figure 2). Within-field variability in EONR was also high, with a range of 80 kg ha^{-1} or more for six of eight fields (Figure 2). The level of between-field and within-field spatial variability in EONR confirms the value of variable-rate N fertilizer application provided that EONR can be accurately predicted across the field.

3.2 | Selection of soil variables for management zone delineation

The first objective of this research was to determine which soil and landscape variables could identify areas with differential crop response to N and could therefore be used to delineate MZs. An analysis of all sites combined (i.e., Global Approach) indicated that no variable was significantly correlated to check yield ($p < 0.10$). Relative elevation and slope were significantly correlated to NDRE ($p < 0.05$), but the correlation was weak ($R = -0.21$ and -0.25, respectively). Check yield and NDRE were significantly correlated to each other ($p < 0.001$; $R = 0.67$). Most of the soil and topographic variables were significantly correlated to one another, with the highest correlation occurring between $\mathrm{EC_s}$ and $\mathrm{EC_d}$ ($R = 0.94$). Shallow $\mathrm{EC_a}$ was significantly correlated ($p < 0.001$) to every other soil and topography variable.

To remove confounding N treatment effects on the correlation between crop and soil variables, a second analysis looked at correlations to in-season NDRE for all but the check plots, which at the time of sensing had an equal rate of N fertilizer applied. Four variables—SOM, $\mathrm{SR_{soil}}$, Slope, and $\mathrm{Elev_{rel}}$—were significantly correlated to NDRE at $p < 0.05$, though weakly ($R = 0.17$, -0.14, -0.14, -0.11). With no significant correlation to check yield and only weak correlations to NDRE, no variable was chosen to cluster MZ in an approach with all fields combined (Global approach). The eight fields chosen varied widely in soil texture, SOM, and topography, making it difficult to explain crop response accurately for all of them using the same one or two soil properties. Correlations were subsequently evaluated on a field-by-field basis (Field-Specific approach).

In the Field-Specific analysis, EC_s was chosen as a clustering variable in five of eight fields (Table 5), and EC_d was chosen as a clustering variable in four of eight fields (Table 5). Soil organic matter was chosen in three of eight fields, and $Elev_{rel}$ was selected in two of eight fields (Table 5). Consistent relationships were not observed between the four field classification groups and the variables chosen for MZ delineation. However, for the four sites where EC_s had a significant ($p < 0.05$) correlation to both check yield and NDRE, the correlations were positive for sites with coarse-textured soils (KR16 and KR17) and negative for sites with fine-textured soils (HU16 and HU17). For the sandy fields, areas with higher soil EC_s had higher clay content, water-holding capacity, and SOM, resulting in improved crop growth. For the silt loam fields, greater EC_s corresponded to areas with higher slopes or with increased clay content and poorer drainage where conditions are less suitable for optimal crop growth in most growing seasons.

No soil or topographic variable was significantly correlated to crop response in an approach using all sites combined. When evaluated on a field-specific basis, soil EC_a had the highest correlations to crop response overall and was used as a clustering variable in five of eight fields. Crop response was correlated to SOM in fields with high variability in SOM and was used as a clustering variable in three of eight fields. Soil organic matter was moderately correlated to both EC_s and EC_d ($R = 0.65; 0.71$), which has also been reported by Serrano et al. (2014).

3.3 | Management zone delineation

After clustering in MZA, the FPI indicated that optimal clustering occurred with five MZs in two fields, with three MZs in two fields, and with two MZs in four fields. For NCE, optimal clustering occurred with two MZs for all eight fields. To simplify analysis, each field was clustered into two MZs.

A map of delineated MZs for Field HU17 is presented in Figure 3. For all sites, Zone 1 consisted of more productive soils with higher SOM content, while Zone 2 classified the less productive areas of the field. For the sandy level fields (KR16 and KR17), Zone 1 contained soils with higher soil EC_a and corresponding higher SOM content. The fields with eroded slopes (CA16, HU16, JA17) had more productive areas in the level, upland positions of the landscape, while Zone 2 areas were associated with steep slopes and drainage areas, and lower SOM, with conditions less suitable for growth. Silt loam level fields (AR16, AR17, and HU17) had more productive Zone 1 areas associated with lower soil EC_a in slight depressions.

3.4 | Management zone validation

3.4.1 | Soil chemical properties

In the analysis of soil chemical properties, the property that exhibited significant ($p < 0.05$) between-zone differences most often was CEC, occurring in five of eight fields (Table 4). Interestingly, CEC was significantly greater in Zone 1 for the fields with coarse-textured soils (KR16 and JA17) and significantly greater in Zone 2 for the fields with fine-textured soils (AR16, HU16, and HU17). This higher CEC for the Zone 1 soils in sandy fields is likely related to higher clay content in these areas given the fact that these fields had positive correlations between crop growth and soil EC_a, while the opposite was true for the silt loam fields (Table 5). Measured SOM recorded significant differences between MZ in three of eight fields. Phosphorus and pH did not prove to be valuable indicators of zonal differences, each returning a significant difference in only one of eight fields.

3.4.2 | Normalized difference red edge index

The second objective of this study was to determine if delineated MZ can identify areas with differential crop response to N fertilizer. Field-Specific MZs were delineated using a combination of EC_a, SOM, and elevation layers. For six of the eight fields, Zone 1 properly identified areas with significantly higher NDRE values and potentially greater N sufficiency than Zone 2 when using the check plots ($p < 0.05$; Figure 4). When all other plots were analyzed, Zone 1 identified areas with significantly higher NDRE values in six of eight fields. When considering both groups (check plots and all other plots), there was a significant difference in NDRE between zones for at least one of the groups for all eight fields.

Results from this study indicate that soil and topographic properties can be used to delineate Field-Specific MZ that properly identify spatial variability in crop response to N measured both in-season (NDRE) and by grain yield, particularly in fields with medium-to-high spatial variability. This is in contrast to results concluded by Inman et al. (2008). However, their study used a different vegetation index, the Normalized Difference Vegetation Index, which, under high-biomass conditions, can become saturated and fail to accurately reflect chlorophyll content (Gitelson & Merzlyak, 1996). They also collected reflectance data using a passive sensor in an aircraft rather than a ground-based active sensor.

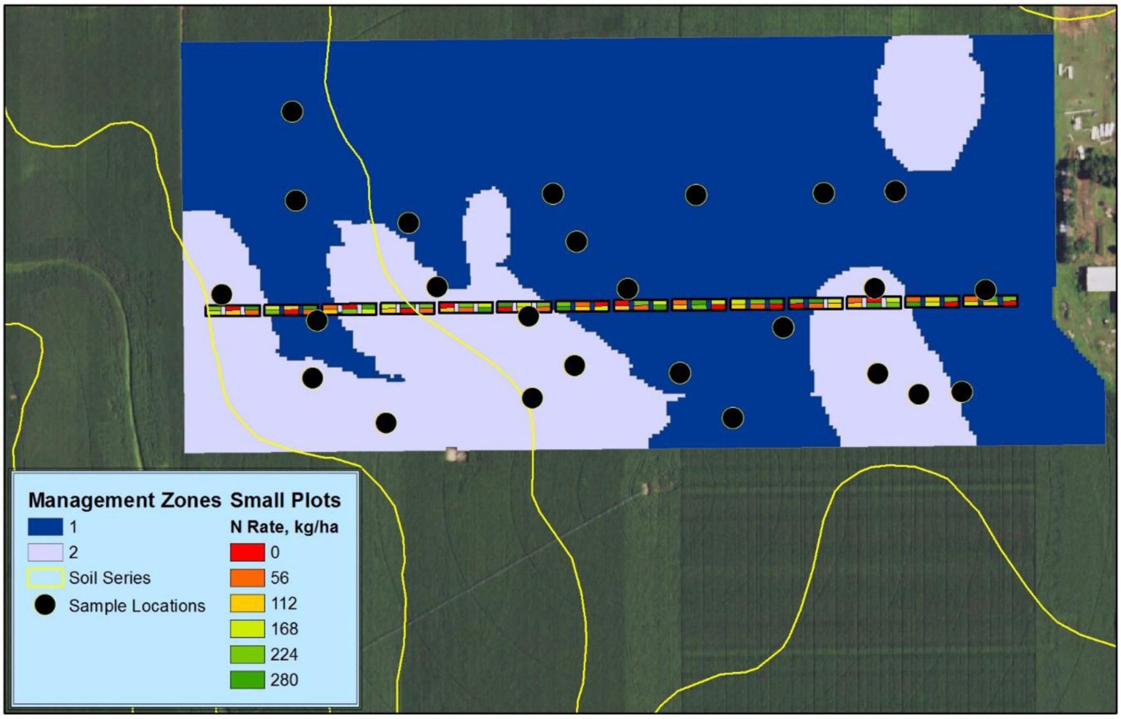

FIGURE 3 Management zone delineation for Field HU17 using EC_s and SOM. EC_s, EC_s shallow; SOM, soil organic matter.

TABLE 4 Soil chemical properties (0–20 cm) for delineated management zone (MZ)

Field	MZ	*n*	pH	Mehlich-III P (Mg kg^{-1})	SOM (g g^{-1})	CEC (cmol$_c$ kg^{-1})
AR16	1	14	6.01	67.6*	3.99	16.7**
	2	11	6.08	29.9*	3.84	20.8**
CA16	1	15	5.94	24.4	3.10	20.5
	2	10	5.98	22.7	2.81	18.4
HU16	1	11	5.79*	46.9	3.17**	14.6**
	2	14	6.07*	55.1	2.69**	18.2**
KR16	1	4	5.98	155.0	1.40**	7.3**
	2	14	5.59	65.6	0.81**	4.4**
AR17	1	19	6.47	14.8	3.05	18.9
	2	6	6.62	7.7	2.78	21.4
HU17	1	15	6.01	23.8	3.41	17.6**
	2	10	6.28	14.8	3.22	19.8**
JA17	1	13	6.05	45.3	1.80**	10.2**
	2	12	6.08	44.3	1.06**	6.7**
KR17	1	9	6.74	17.1	1.38	8.0
	2	16	6.72	25.3	1.08	6.1

Note: Statistically different MZs are indicated with the appropriate significance level indicator.
Abbreviations: CEC, cation exchange capacity; SOM, soil organic matter.
*Statistical significance at $p < 0.05$.
**Statistical significance at $p < 0.01$.

TABLE 5 Pearson correlation coefficients (R) of soil and topographic variables to check plot yield and normalized difference red edge (NDRE) for all site-years (Field-Specific approach)

				Electrical conductivity		Soil optical reflectance		Landscape	
Field	**Crop parameter**	**N rate (kg ha^{-1})**	***n***	**EC_s**	**EC_d**	**SR_{soil}**	**SOM**	**$Elev_{rel}$**	**Slope**
AR16	NDRE	84	60	**−0.66*****	**−0.61*****	0.25	0.43**	−0.56***	−0.34**
	Yield	84	10	**0.46**	**0.41**	−0.30	−0.40	0.28	0.21
CA16	NDRE	56	65	0.07	−0.06	0.01	0.06	**0.23**	−0.15
	NDRE	0	13	0.55	0.41	−0.20	0.36	**0.60***	−0.32
	Yield	0	13	0.43	0.41	0.30	−0.12	**0.43**	−0.18
HU16	NDRE	56	75	**−0.60*****	**−0.57*****	0.38***	0.41***	0.35**	−0.35**
	NDRE	0	12	**−0.63***	**−0.78****	0.44	0.52	0.51	−0.52
	Yield	0	12	**−0.64***	**−0.80****	0.42	0.51	0.46	−0.44
KR16	NDRE	56	80	**0.69*****	**0.66*****	−0.55***	–	0.14	0.05
	NDRE	0	16	**0.83*****	**0.67****	−0.65**	–	0.15	−0.17
	Yield	0	16	**0.91*****	**0.72****	−0.74**	–	0.22	−0.08
AR17	NDRE	56	52	−0.22	−0.18	−0.08	**0.16**	**−0.12**	0.14
	NDRE	0	11	−0.40	−0.27	0.44	**0.30**	**−0.77****	−0.23
	Yield	0	11	−0.55	−0.35	−0.24	**0.62***	**−0.36**	−0.36
HU17	NDRE	56	70	**−0.57*****	−0.34**	0.12	**0.68*****	−0.39**	−0.63***
	NDRE	0	14	**−0.79*****	−0.62*	−0.07	**0.73****	−0.40	−0.56*
	Yield	0	14	**−0.79*****	−0.56*	0.07	**0.73****	−0.21	−0.64*
JA17	NDRE	56	80	0.35**	0.18	−0.49***	**0.50*****	−0.14	−0.18
	NDRE	39	16	0.40	0.31	−0.47	**0.47**	−0.30	−0.45
	Yield	39	16	0.19	0.27	0.07	**−0.02**	−0.20	−0.15
KR17	NDRE	80	80	**0.45*****	**0.26***	−0.30**	0.44***	0.12	−0.36**
	NDRE	24	16	**0.53***	**0.46**	−0.52*	0.50*	−0.14	−0.54*
	Yield	24	16	**0.85*****	**0.84*****	−0.08	−0.03	0.42	0.22

Note: Bold values indicate select variables used in management zone delineation.

Abbreviations: EC_d, apparent electrical conductivity, deep; EC_s, apparent electrical conductivity, shallow; $Elev_{rel}$, relative elevation; SR_{soil}, simple ratio (NIR/red); SOM, soil organic matter.

*Statistical significance at $p < 0.05$.

**Statistical significance at $p < 0.01$.

***Statistical significance at $p < 0.001$.

3.4.3 | Yield

Yield responses to N rate models in Zones 1 and 2 were significantly different ($p < 0.05$) for Fields KR16, HU17, and KR17 (Figure 5). They were not significantly different for Fields AR16, CA16, and AR17, and comparisons could not be made in Fields HU16 and JA17. For these two fields (HU16 and JA17), all blocks showing a quadratic-plateau response were located in one zone. Fields AR16 and AR17 had very little variability, and each field contained highly productive soils across both zones. This resulted in very small differences between zones in optimal yield (0.61 and 0.01 Mg ha^{-1}, respectively) and EONR (23 and 11 kg ha^{-1}, respectively) (Table 6). While the models for Zones 1 and 2 in Field CA16 were not significantly different ($p = 0.058$), zonal EONR varied by 96 kg ha^{-1}, the greatest range in EONR for any of the fields studied.

Maximum yield difference between zones was greatest in Field KR16 (3.46 Mg ha^{-1}) and Field KR17 (2.39 Mg ha^{-1}). Though these fields had a very great difference in optimum yield, there were minimal differences in EONR between zones (11 and 28 kg ha^{-1} for Fields KR16 and KR17, respectively). Zone 1 for both of these fields contained areas with more productive soil, resulting in significantly increased yields compared to Zone 2. However, because the soil was likely supplying more N in these favorable conditions, less N was required from N fertilizer additions (Morris et al., 2018). This can also be confirmed by the fact that for four of six fields in this study, Zone 2 EONR was greater than EONR for Zone 1. The results from this study indicate that soil-based MZ delineated using Field-Specific variables are able to appropriately classify areas with differing yield response to N rate in fields with medium-to-high spatial variability. Accounting for this within-field variability through the use of soil-based

TABLE 6 Yield response to N rate models by zone

Field	Zone	Quadratic model			N rate at max yield (kg ha^{-1})	Max yield (Mg ha^{-1})	EONR (kg ha^{-1})	Yield at EONR (Mg ha^{-1})	RMSE	r^2	Difference between zones[a]
		a	b	c							
AR16	1	7.75	0.0663	−0.000154	216	14.90	189	14.79	0.32	0.93	NS
	2	7.62	0.0708	−0.000188	188	14.27	166	14.18	0.46	0.80	
CA16	1	7.02	0.0918	−0.000519	88	11.08	80	11.05	0.10	1.00	NS
	2	6.23	0.0496	−0.000117	212	11.48	176	11.33	0.52	0.95	
HU16	1	–	–	–	–	–	–	–	–	–	–
	2	9.78	0.0921	−0.000396	116	15.14	106	15.10	0.14	1.00	
KR16	1	10.79	0.0438	−0.000093	235	15.93	191	15.75	0.44	0.96	***
	2	5.88	0.0552	−0.000116	238	12.44	202	12.29	0.10	1.00	
AR17	1	10.84	0.0606	−0.000253	120	14.47	103	14.40	0.25	0.98	NS
	2	10.17	0.0659	−0.000253	130	14.46	114	14.39	0.36	0.97	
HU17	1	12.11	0.1027	−0.000586	88	16.61	81	16.58	0.11	1.00	**
	2	9.68	0.0874	−0.000302	145	16.00	131	15.94	0.43	0.98	
JA17	1	10.47	0.0669	−0.000150	223	17.94	196	17.83	0.57	0.95	–
	2	–	–	–	–	–	–	–	–	–	
KR17	1	10.39	0.0539	−0.000135	199	15.76	169	15.63	0.42	0.95	***
	2	7.43	0.0750	−0.000236	159	13.37	141	13.30	0.28	0.98	

Note: Fields HU16 and JA17 did not have any blocks fitting a quadratic-plateau function in one of their zones; therefore, comparisons could not be made.

Abbreviations: EONR, economic optimum N rate; RMSE, root mean square error.

[a]NS, not significant at $\alpha = 0.05$.

**Statistical significance at $p < 0.01$.

***Statistical significance at $p < 0.001$.

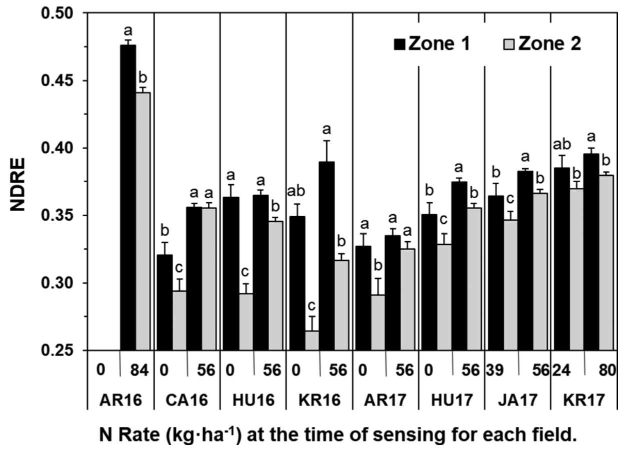

FIGURE 4 In-season canopy reflectance (NDRE) by N rate by zone for each field. Bars with the same letter are not significantly different. Error bars represent standard error for each treatment. NDRE, normalized difference red edge.

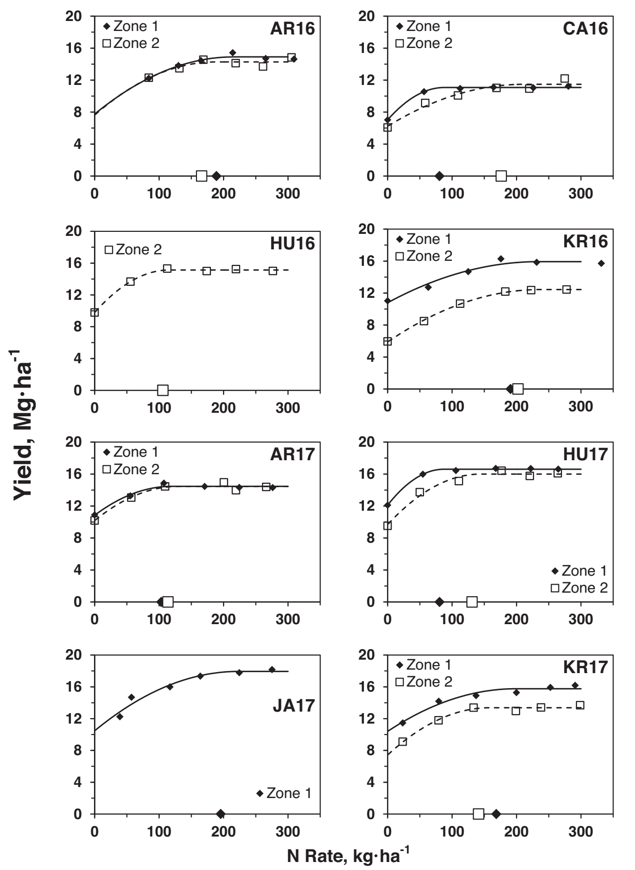

FIGURE 5 Yield response to N rate by zone within each field. Zones 1 and 2 economic optimum N rate (EONR) is designated on the *x*-axis with the corresponding zone symbol.

MZ has potential to increase the performance of sensor-based N recommendation algorithms.

3.4.4 | Economic considerations

An economic analysis compared current producer N fertilizer application rates for each field (from Table 2) to applying a zone-based uniform N rate based on the calculated EONR for each zone. This analysis was performed for the six fields for which quadratic-plateau functions for yield response to N were fitted by zone. The study areas in Fields AR16, CA16, KR16, AR17, HU17, and KR17 were 29.6, 12.8, 14.8, 18.7, 24.2, and 16.4 ha, respectively. Assuming an N fertilizer cost of \$0.99 kg^{-1}, the potential savings or loss resulting from zone-based application was determined. There was a total savings/loss of \$16 ha^{-1}, \$117 ha^{-1}, −\$11 ha^{-1}, \$95 ha^{-1}, \$137 ha^{-1}, and \$92 ha^{-1} for Fields AR16, CA16, KR16, AR17, HU17, and KR17, respectively. Extrapolating this savings to a typical center pivot in Nebraska with an area of ∼60 ha, the savings/loss was \$982, \$6991, −\$681, \$5674, \$8244, and \$5505 for these fields. The loss on Field KR16 was due to the EONR for both zones being greater than the producer's uniform N rate. The substantial economic benefit measured in five of six fields analyzed suggests a potential benefit to applying N fertilizer according to delineated MZ. In addition, EONR varied greatly among and within fields in this study. Sub-field EONR exceeded 80 kg N ha^{-1} for six of the total eight fields. The high level of spatial variability in EONR confirms the value of variable-rate N fertilizer application if EONR can be accurately predicted across the field as suggested by Holland and Schepers (2010) and Solari et al. (2008).

The economic analysis showed a potential benefit to variable-rate N fertilizer applications using soil-based MZ compared to a uniform rate in five of six fields analyzed, echoing the potential for improved on-farm economics using these methods suggested by Roberts et al. (2012). Further economic benefits may be achieved by integrating MZ and sensor-based N management. It is clear that defining an accurate EONR continues to be challenging, and potential studies using previous yield history and modeling techniques may improve those estimates, which is critical to sensor-based N management approaches. While this study and the study by Roberts et al. (2012) were performed in irrigated fields, further research into rainfed environments—while more challenging for predicting EONR—should be conducted.

4 | CONCLUSIONS

This study sought to identify relationships among maize response variables and measured soil and topographic attributes (for developing MZs) from eight irrigated maize fields in central Nebraska in 2016 and 2017. Yield response to

N rate was highly variable among and within fields, as were economic optimum N rates, which ranged 80 kg N ha^{-1} or more for six of eight fields. Soil EC_a had the highest correlations to crop response overall and was used as a clustering variable in five of eight fields. Economic analysis showed a potential advantage to using soil-based MZ compared to producer-chosen uniform N rates in five of six fields. Delineated MZs were able to identify areas with differential soil properties and crop response to N fertilizer. Integrating soil-based MZ and sensor-based N management has potential to achieve further economic benefits.

AUTHOR CONTRIBUTIONS

Joel Crowther: Conceptualization; Data curation; Formal analysis; Investigation; Methodology; Writing – original draft. **John Parrish**: Formal analysis; Investigation; Methodology. **Joe Luck**: Funding acquisition; Methodology; Project administration; Resources; Supervision; Writing – review & editing. **Richard Ferguson**: Conceptualization; Funding acquisition; Methodology; Project administration; Resources; Supervision; Writing – review & editing.

ACKNOWLEDGMENTS

This work is supported by the Critical Agriculture Research and Extension program, grant No. 2015-67029-23517/project accession No. 1006193 from the USDA National Institute of Food and Agriculture. The authors would also like to acknowledge the financial support of the United States Department of Agriculture National Institute of Food and Agriculture, Hatch Project #1009760. Any opinions, findings, conclusions, or recommendations expressed in this publication are those of the author(s) and do not necessarily reflect the view of the U.S. Department of Agriculture.

CONFLICT OF INTEREST STATEMENT

The authors declare no conflict of interest.

REFERENCES

Adamchuk, V. I., Viscarra Rossel, R. A., Sudduth, K. A., & Lammers, P. S. (2011). Sensor fusion for precision agriculture. In C. Thomas (Ed.), *Sensor fusion—Foundation and applications* (pp. 27–40). InTech.

Amaral, L. R., Molin, J. P., & Schepers, J. S. (2015). Algorithm for variable-rate nitrogen application in sugarcane based on active crop canopy sensor. *Agronomy Journal*, *107*, 1513–1523. https://doi.org/10.2134/agronj14.0494

Cassman, K. G., Dobermann, A. R., & Walters, D. T. (2002). Agroecosystems, nitrogen-use efficiency, and nitrogen management. *Ambio: A Journal of the Human Environment*, *31*, 132–140. https://doi.org/10.1579/0044-7447-31.2.132

Cerrato, M. E., & Blackmer, A. M. (1990). Comparison of models for describing corn yield response to nitrogen fertilizer. *Agronomy Journal*, *82*, 138–143. https://doi.org/10.2134/agronj1990.00021962008200010030x

Chow, G. C. (1960). Tests of equality between sets of coefficients in two linear regressions. *Econometrica*, *28*, 591–605. https://doi.org/10.2307/1910133

Ciampitti, I. A., & Vyn, T. J. (2011). A comprehensive study of plant density consequences on nitrogen uptake dynamics of maize plants from vegetative to reproductive stages. *Field Crops Research*, *121*, 2–18. https://doi.org/10.1016/j.fcr.2010.10.009

Doerge, T. (1999). Defining management zones for precision farming. In *Crop insight* (Vol. 8, p. 21). Pioneer Hi-Bred International, Inc.

Fageria, N. K., & Baligar, V. C. (2005). Enhancing nitrogen use efficiency in crop plants. *Advances in Agronomy*, *88*, 97–185. https://doi.org/10.1016/S0065-2113(05)88004-6

Fleming, K. L., Heermann, D. F., & Westfall, D. G. (2004). Evaluating soil color with farmer input and apparent soil electrical conductivity for management zone delineation. *Agronomy Journal*, *96*, 1581–1587. https://doi.org/10.2134/agronj2004.1581

Flowers, M., Weisz, R., & White, J. G. (2005). Yield-based management zones and grid sampling strategies: Describing soil test and nutrient variability. *Agronomy Journal*, *97*, 968–982. https://doi.org/10.2134/agronj2004.0224

Fraisse, C. W., Sudduth, K. A., & Kitchen, N. R. (2001). Delineation of site-specific management zones by unsupervised classification of topographic attributes and soil electrical conductivity. *Transactions of the American society of agricultural engineers* Vol. 44, pp. 155–166. American Society of Agricultural Engineers.

Franzen, D., Sharma, L. K., & Bu, H. (2014). *Active optical sensor algorithms for corn yield prediction and a corn side-dress nitrogen rate aid. Extension circular SF1176-5*. North Dakota State University Extension Service.

Franzen, D. W., Hopkins, D. H., Sweeney, M. D., Ulmer, M. K., & Halvorson, A. D. (2002). Evaluation of soil survey scale for zone development of site-specific nitrogen management. *Agronomy Journal*, *94*, 381–389.

Fridgen, J. J., Kitchen, N. R., Sudduth, K. A., Drummond, S. T., Wiebold, W. J., & Fraisse, C. W. (2004). Management zone analyst (MZA): Software for subfield management zone delineation. *Agronomy Journal*, *96*, 100–108.

Gitelson, A. A., & Merzlyak, M. N. (1994). Quantitative estimation of chlorophyll-a using reflectance spectra: Experiments with autumn chestnut and maple leaves. *Journal of Photochemistry and Photobiology*, *22*, 247–252. https://doi.org/10.1016/1011-1344(93)06963-4

Gitelson, A. A., & Merzlyak, M. N. (1996). Signature analysis of leaf reflectance spectra: Algorithm development for remote sensing of chlorophyll. *Journal of Plant Physiology*, *148*, 494–500. https://doi.org/10.1016/S0176-1617(96)80284-7

Hatfield, J. L., Gitelson, A. A., Schepers, J. S., & Walthall, C. L. (2008). Application of spectral remote sensing for agronomic decisions. *Agronomy Journal*, *100*, 117–131. https://doi.org/10.2134/agronj2006.0370c

Holland, K. H., & Schepers, J. S. (2010). Derivation of a variable rate nitrogen application model for in-season fertilization of corn. *Agronomy Journal*, *102*, 1415–1424. https://doi.org/10.2134/agronj2010.0015

Inman, D., Khosla, R., Reich, R., & Westfall, D. G. (2008). Normalized difference vegetation index and soil color-based management zones in irrigated maize. *Agronomy Journal*, *100*, 60–66. https://doi.org/10.2134/agronj2007.0020

Khosla, R., Westfall, D. G., Reich, R. M., Mahal, J. S., & Gangloff, W. J. (2010). Spatial variation and site-specific management zones. In M. A. Oliver (Ed.), *Geostatistical applications in precision agriculture* (pp. 195–219). Springer.

Kitchen, N. R., Sudduth, K. A., & Drummond, S. T. (1999). Soil electrical conductivity as a crop productivity measure for claypan soils. *Journal of Production Agriculture*, *12*, 607–617. https://doi.org/10.2134/jpa1999.0607

Kitchen, N. R., Sudduth, K. A., Drummond, S. T., Scharf, P. C., Palm, H. L., Roberts, D. F., & Vories, E. D. (2010). Ground-based canopy reflectance sensing for variable-rate nitrogen corn fertilization. *Agronomy Journal*, *102*, 71–84. https://doi.org/10.2134/agronj2009.0114

Kweon, G., Lund, E., & Maxton, C. (2013). Soil organic matter and cation-exchange capacity sensing with on-the-go electrical conductivity and optical sensors. *Geoderma*, *199*, 80–89. https://doi.org/10.1016/j.geoderma.2012.11.001

Lark, R. M., & Stafford, J. V. (1997). Classification as a first step in the interpretation of temporal and spatial variation of crop yield. *Annals of Applied Biology*, *130*, 111–121. https://doi.org/10.1111/j.1744-7348.1997.tb05787.x

Li, F., Miao, Y., Feng, G., Yuan, F., Yue, S., Gao, X., Liu, Y., Liu, B., Ustin, S. L., & Chen, X. (2014). Improving estimation of summer maize nitrogen status with red edge-based spectral vegetation indices. *Field Crops Research*, *157*, 111–123. https://doi.org/10.1016/j.fcr.2013.12.018

Merrick & Co. (2011). NRCS LiDAR DEMs for eastern Nebraska—2 meter—2010. Nebraska Department of Natural Resources. https://dnr.nebraska.gov/data/elevation-data

Morris, T. F., Murrell, T. S., Beegle, D. B., Camberato, J. J., Ferguson, R. B., Grove, J., Ketterings, Q., Kyveryga, P. M., Laboski, C. A. M., McGrath, J. M., Meisinger, J. J., Melkonian, J., Moebius-Clune, B. N., Nafziger, E. D., Osmond, D., Sawyer, J. E., Scharf, P. C., Smith, W., Spargo, J. T., … Yang, H. (2018). Strengths and limitations of nitrogen rate recommendations for corn and opportunities for improvement. *Agronomy Journal*, *110*, 1–37. https://doi.org/10.2134/agronj2017.02.0112

NDEE (Nebraska Department of Environment and Energy). (2019). 2019 Nebraska Groundwater Quality Monitoring Report. http://dee.ne.gov/Publica.nsf/Pages/WAT333

Odeh, I. O. A., McBratney, A. B., & Chittleborough, D. J. (1992). Soil pattern recognition with fuzzy c-means: Application to classification and soil-landform interrelationships. *Soil Science Society of America Journal*, *56*, 505–516. https://doi.org/10.2136/sssaj1992.03615995005600020027x

Oliveira, L. F., Scharf, P. C., Vories, E. D., Drummond, S. T., Dunn, D., Stevens, W. G., Bronson, K. F., Benson, N. R., Hubbard, V. C., & Jones, A. S. (2013). Calibrating canopy reflectance sensors to predict optimal mid-season nitrogen rate for cotton. *Soil Science Society of America Journal*, *77*, 173–183. https://doi.org/10.2136/sssaj2012.0154

Peterson, T. A., Blackmer, T. M., Francis, D. D., & Schepers, J. S. (1993). *Using a chlorophyll meter to improve N management. Nebguide G93-1171-A*. Cooperative Extension Service, University of Nebraska-Lincoln.

Ping, J. L., Ferguson, R. B., & Dobermann, A. (2008). Site-specific nitrogen and plant density management in irrigated maize. *Agronomy Journal*, *100*, 1193–1204. https://doi.org/10.2134/agronj2007.0174

Raun, W. R., Solie, J. B., Johnson, G. V., Stone, M. L., Mullen, R. W., Freeman, K. W., Thomason, W. E., & Lukina, E. V. (2002). Improving nitrogen use efficiency in cereal grain production with optical sensing and variable rate application. *Agronomy Journal*, *94*, 815–820. https://doi.org/10.2134/agronj2002.8150

Roberts, D. F., Ferguson, R. B., Kitchen, N. R., Adamchuk, V. I., & Shanahan, J. F. (2012). Relationships between soil-based management zones and canopy sensing for corn nitrogen management. *Agronomy Journal*, *104*, 119–129. https://doi.org/10.2134/agronj2011.0044

Roberts, D. F., Kitchen, N. R., Scharf, P. C., & Sudduth, K. A. (2010). Will variable-rate nitrogen fertilization using corn canopy reflectance sensing deliver environmental benefits? *Agronomy Journal*, *102*, 85–95. https://doi.org/10.2134/agronj2009.0115

Scharf, P. C., Kitchen, N. R., Sudduth, K. A., Davis, J. G., Hubbard, V. C., & Lory, J. A. (2005). Field-scale variability in optimal nitrogen fertilizer rate for corn. *Agronomy Journal*, *97*, 452–461. https://doi.org/10.2134/agronj2005.0452

Scharf, P. C., Shannon, D. K., Palm, H. L., Sudduth, K. A., Drummond, S. T., Kitchen, N. R., Mueller, L. J., Hubbard, V. C., & Oliveira, L. F. (2011). Sensor-based nitrogen applications out-performed producer-chosen rates for corn in on-farm demonstrations. *Agronomy Journal*, *103*, 1683–1691. https://doi.org/10.2134/agronj2011.0164

Schepers, A. R., Shanahan, J. F., Liebig, M. A., Schepers, J. S., Johnson, S. H., & Luchiari, A., Jr. (2004). Appropriateness of management zones for characterizing spatial variability of soil properties and irrigated corn yields across years. *Agronomy Journal*, *96*, 195–203. https://doi.org/10.2134/agronj2004.1950

Serrano, J., Shahidian, S., & Silva, M. D. J. (2014). Spatial and temporal patterns of apparent electrical conductivity: DUALEM vs. Veris sensors for monitoring soil properties. *Sensors*, *14*, 10024–10041. https://doi.org/10.3390/s140610024

Shahandeh, H., Wright, A. L., Hons, F. M., & Lascano, R. J. (2005). Spatial and temporal variation of soil nitrogen parameters related to soil texture and corn yield. *Agronomy Journal*, *97*, 772–782. https://doi.org/10.2134/agronj2004.0287

Shanahan, J. F., Kitchen, N. R., Raun, W. R., & Schepers, J. S. (2008). Responsive in-season nitrogen management for cereals. *Computers and Electronics in Agriculture*, *61*, 51–62. https://doi.org/10.1016/j.compag.2007.06.006

Snyder, C. S. (2012). Are Midwest corn farmers over-applying fertilizer N? *Better Crops with Plant Food*, *96*, 3–4.

Solari, F., Shanahan, J., Ferguson, R., Schepers, J., & Gitelson, A. (2008). Active sensor reflectance measurements of corn nitrogen status and yield potential. *Agronomy Journal*, *100*, 571–579. https://doi.org/10.2134/agronj2007.0244

Solie, J. B., Monroe, A. D., Raun, W. R., & Stone, M. L. (2012). Generalized algorithm for variable-rate nitrogen application in cereal grains. *Agronomy Journal*, *104*, 378–387. https://doi.org/10.2134/agronj2011.0249

Tremblay, N., Bouroubi, Y. M., Bélec, C., Mullen, R. W., Kitchen, N. R., Thomason, W. E., Ebelhar, S., Mengel, D. B., Raun, W. R., Francis, D. D., Vories, E. D., & Ortiz-Monasterio, I. (2012). Corn response to nitrogen is influenced by soil texture and weather. *Agronomy Journal*, *104*, 1658–1671. https://doi.org/10.2134/agronj2012.0184

Tubaña, B. S., Harrell, D. L., Walker, T., Teboh, J., Lofton, J., & Kanke, Y. (2012). In-season canopy reflectance-based estimation of rice yield response to nitrogen. *Agronomy Journal*, *104*, 1604–1611. https://doi.org/10.2134/agronj2012.0214

Walburg, G., Bauer, M. E., Daughtry, C. S. T., & Housley, T. L. (1982). Effects of nitrogen nutrition on the growth, yield, and reflectance characteristics of corn canopies. *Agronomy Journal*, *74*, 677–683. https://doi.org/10.2134/agronj1982.00021962007400040020x

How to cite this article: Crowther, J., Parrish, J., Luck, J. D., & Ferguson, R. B. (2023). Evaluating management zones and crop-sensing relationships for improved irrigated maize nitrogen management. *Agrosystems, Geosciences & Environment*, *6,* e20336. https://doi.org/10.1002/agg2.20336