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RESEARCH ARTICLE

An integrated approach to site-specific management zone delineation

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Abstract Dividing fields into a few relatively homogeneous management zones (MZs) is a practical and cost-effective approach to precision agriculture. There are three basic approaches to MZ delineation using soil and/or landscape properties, yield information, and both sources of information. The objective of this study is to propose an integrated approach to delineating site-specific MZ using relative elevation, organic matter, slope, electrical conductivity, yield spatial trend map, and yield temporal stability map (ROSE-YSTTS) and evaluate it against two other approaches using only soil and landscape information (ROSE) or clustering multiple year yield maps (CMYYM). The study was carried out on two no-till corn-soybean rotation fields in eastern Illinois, USA. Two years of nitrogen (N) rate experiments were conducted in Field B to evaluate the delineated MZs for site-specific N management. It was found that in general the ROSE approach was least effective in accounting for crop yield variability (8.0%–9.8%), while the CMYYM approach was least effective in accounting for soil and landscape (8.9%–38.1%), and soil nutrient and pH variability (9.4%–14.5%). The integrated ROSE-YSTTS approach was reasonably effective in accounting for the three sources of variability (38.6%–48.9%, 16.1%–17.3% and 13.2%–18.7% for soil and landscape, nutrient and pH, and yield variability, respectively), being either the best or second best approach. It was also found that the ROSE-YSTTS approach was effective in defining zones with high, medium and low economically optimum N rates. It is concluded that the integrated ROSE-YSTTS approach combining soil, landscape and yield spatial-temporal variability information can overcome the weaknesses of approaches using only soil, landscape or yield information, and is more robust for MZ delineation. It also has the potential for site-specific N management for improved economic returns. More studies are needed to further evaluate their appropriateness for precision N and crop management.

Keywords economically optimum nitrogen rate, fuzzy cluster analysis, precision nitrogen management, site-specific management, soil landscape property, yield map

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1 Introduction

World agriculture is facing a great challenge to ensure food security for a population to exceed 9 billion using shrinking crop land and limited resources while protecting the environment[1–3]. Precision agriculture is a promising approach for food security and sustainable development[4–6]. However, the adoption of precision agriculture has been slower than initially expected, due to significant socioeconomic, agronomic and technological challenges[7]. A practical approach that may promote the adoption of precision agriculture is to divide the field into several management zones (MZs). These are subregions of a field that have unique yet relatively homogeneous soil or landscape conditions, and a combination of yield limiting factors that can be managed uniformly with a single rate of crop input or single set of management practices[8,9]. After the MZs are successfully defined, they can be used for zone sampling to save cost and time, and managed for fertility (e.g., fertilizer), soil (e.g., tillage), water (e.g., irrigation) and crop (e.g., planting density) factors[10–12]. MZs may also facilitate the application of crop growth modeling in precision farming[13–15].

Three basic approaches have been developed for site-specific MZ delineation. The first is based on soil and/or landscape information, including soil survey maps[16], invasive soil sampling[17,18], noninvasive soil sampling using electrical conductivity (EC)[19], soil organic matter (OM) or organic carbon estimated using remote sensing images[20], landscape properties[16] and both soil and landscape factors[21–23].

The second approach is based on crop yield maps. Blackmore[24] proposed an empirical procedure to classify yield maps into three classes of management map based on spatial yield trend map (averaged normalized yield map) and temporal stability map [coefficient of variation (CV) map]: high yielding and stable zone, low yielding and stable zone, and unstable zone. An alternative approach to analyzing multi-year yield maps is to use pattern recognition techniques to divide a field into distinctive yield zones, mainly using (fuzzy) cluster analysis[25,26]. It was recommended that cluster analysis of relative average yield over at least five years should be used for yield zone delineation in irrigated fields[27].

The third approach is an integrated one, utilizing both soil or landscape and crop yield information. Taylor et al.[28] used six years of yield maps, soil EC and elevation data to create MZ. Hornung et al.[29] proposed an integrated method of site-specific MZ delineation using multispectral bare soil image, soil OM, soil cation exchange capacity (CEC), soil texture (sand, silt and clay content) and previous year crop yield map.

It is hypothesized that the integrated MZ delineation approach will be more stable and robust in accounting for soil, landscape and yield variability than approaches using a single source of information. However, studies that explicitly evaluate these different MZ delineation approaches are still limited. Therefore, the objective of this study is to propose an integrated approach to define MZs using relative elevation, soil OM, slope, EC, yield spatial trend map, and yield temporal stability map (ROSE-YSTTS) and evaluate it against two other approaches to MZ delineation: using relative elevation, OM, slope and EC (ROSE), and fuzzy clustering multiple year yield maps (CMYYM).

2 Materials and methods

2.1 Study site

This study was conducted on two production fields in Paris, Illinois, USA. Both fields have been in a corn-soybean rotation for many years and under no-till management since 1991. Field A is about 32.8 hm^2 with a 4.57 m difference in relative elevation. It is composed of two principal soil mapping units: Flanagan silt loam (fine, smectitic, mesic Aquertic Argiudolls) in the west half of the field, and Drummer silty clay loam (fine-silty, mixed, mesic Typic Endoaquolls) in the east half. A fence in the middle of the field (Fig. 1a) previously divided it into east and west halves and they were managed separately as two fields. This fence was removed in the 1980s. The east half of the field was also divided by another fence into south and north halves and farmed as such until 1980. It was removed in the 1960s. Field B is 12.5 hm^2, and has a relative elevation difference of 1.97 m. There are three dominant soils in this field; Drummer silty clay loam, Brenton silt loam (fine-silty, mixed, mesic, Aquic Argiudolls), and Raub silt loam (fine-silty, mixed, mesic, Aquic Argiudolls). Manure from a hog house pit was applied to this field every other year between 1978 and 1996. This field used to be separated by a fence in the middle and managed as such until the 1970s. The north-west corner of the field was part of a pasture area before 1950 (Fig. 1b). Subsurface tile drainage has been installed in both fields (Fig. 1).

2.2 Data collection and analysis

Grain yield has been measured since 1995 using a combine equipped with a differential global position systems (DGPS) receiver and an AgLeader yield monitor (AgLeader Technology, Ames, IA, USA). After harvest in the year 2000, one soil sample was per 0.3 hm^2 in Field A and per 0.4 hm^2 in Field B, and analyzed for soil OM, CEC, soil test P (Bray-P), K, S, Zn and pH by A & L Great Lakes Laboratory (Fort Wayne, IN, USA). During soil sampling, elevation and EC data were collected from these two fields using high accuracy DGPS and a Geonics EM-38 instrument (Geonics Ltd, Mississauga, ON, Canada). The data were collected at about 6 m intervals separated by 20 m. The EM 38 instrument was set to the vertical dipole mode with an effective measurement depth of about 0.9 m.

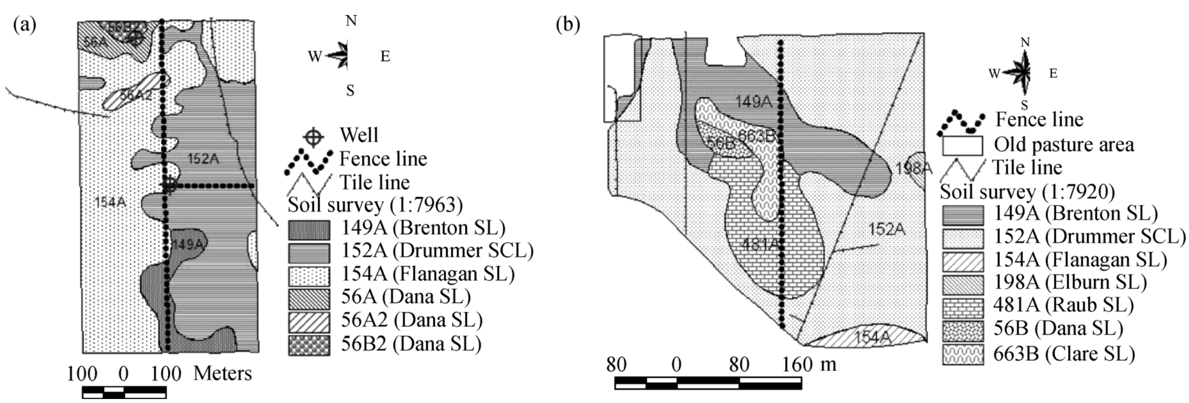

Fig. 1 Order 1 soil survey maps (1:8000) conducted by the United States Department of Agriculture-Natural Resource Conservation Service (USDA-NRCS) in Illinois and field history information of Fields A (a) and B (b).

Soil test data were all interpolated to a 5 m grid using kriging, inverse distance weighting (IDW) or radial basis function interpolation methods, depending on the spatial structures and cross-validation results. The elevation data were used to create a 5-m digital elevation model using the TOPOGRID command in Arc/Info workstation (ESRI, Redlands, CA, USA). Slope was calculated from the model using the CURVATURE command.

Raw crop yield data were cleaned based on standard deviation, field position, and flow rate to remove problem data. Then the data were interpolated to a 5-m grid using kriging or IDW, depending on spatial structures and cross-validation results. The yield maps were normalized by dividing the yield value in each grid cell by the average yield for the entire field for a given year and multiplying by 100%. In 2000, two hybrids (33G26 and 33Y18) were planted side-by-side using a split-planter comparison technique in Field A, so two separate normalized yield maps were created for that year. The normalization procedure was performed to eliminate yield variability due to crop (corn vs. soybean) and hybrid (33Y18 and 33G26) differences. Then the normalized yield maps were used to produce a yield spatial trend map (average yield across 6 years) and a yield temporal stability map (CV map) following Blackmore[24].

2.3 Management zone delineation

The fuzzy cluster analysis algorithm available in Management Zone Analyst[30] was used to classify soil, landscape and/or yield data into two to eight management zones. The appropriate number of MZ was determined according to the results of a fuzziness performance index and normalized classification entropy. Subjective judgment was also used so that the same number of MZs (five and four for Field A and B, respectively) could be selected for different approaches to facilitate comparison.

Based on some previous analyses[31], three approaches to MZ delineation were evaluated. Approach one used ROSE. Approach two used six normalized yield maps; this method involved CMYYM. Approach three was an integrated one termed ROSE-YSTTS. A combination of three grid generalization techniques (majority filtering, noise removal and edge smoothing) was used to smooth the created MZs.

Relative variance (RV) was used in this study to evaluate the accuracy of different approaches for delineating management zones, and RV is given by:

$$\mathrm{RV} = 1 - S_{\mathrm{w}}^2 / S_{\mathrm{T}}^2 \tag{1}$$

where S_{w}^2 is the total within-zone variance of soil and landscape properties, soil nutrients, or crop yield. S_{T}^2 is total field variance of the corresponding property.

RV reflects the amount of variability explained by the MZ delineation, and can be interpreted similar to the R^2 value of regression[27], i.e., the higher the RV value, the greater the amount of variability that is explained by the MZ delineation. The approach that accounts for the most soil, landscape or yield variability is the best approach.

2.4 Management zone evaluation for site-specific nitrogen management

On-farm N experiments were conducted in 2001 and 2003 in Field B. Four replications of five side-dressed N rate treatments (as anhydrous NH3) were established in early June in a split-plot design. The main plot consisted of five N rates: 0, 112, 168, 224 and 337 kg·hm^{-2} N. Each N rate was randomly assigned to 18.24-m wide strips running across the length of the whole field. The subplot treatments were two corn hybrids; Pioneer 33G26 [relative maturity (RM) 112 d] and 33J24 (RM 112 d). The hybrids were planted side-by-side using the split-planter comparison technique (systematic rather than random arrangement). The planting rates were about 76600 seed per hm^2. Scouting was conducted on a regular basis during the growing seasons and no major pests were found to be a serious problem. P and K fertilizers were applied using variable rate technology to compensate for any P and K deficiencies in the study fields based on 0.4-hm^2 grid point sampling results and fertilizer application was performed by local fertilizer dealers.

Before harvest, five transects across all N x hybrid treatments were superimposed over the experimental site to determine sampling locations. The average spacing between transects was about 50 m. At each sampling point, five consecutive corn ears (8–10 ears for control strips) were hand collected. A total of 190 samples were collected (samples were collected only on four transects in the fourth replication or block due to field dimension limitation) each year for corn quality determination (data not used for the MZ analysis). Corn yield was measured using a combine equipped with a calibrated AgLeader yield monitor (AgLeader Technology, Ames, IA, USA). Yield data were cleaned by removing yield points that were near the start or end of harvest passes, and removing yield values or grain flow rates that exceeded three standard deviations; however, yield values exceeding three standard deviations in check strips (with no N application) were not removed. The two closest yield points were averaged to represent the yield at each corn quality sampling location. Corn yield N response curves at selected within-field locations were generated using the NLIN procedure in SAS (SAS Inst., 1998). Four different N response models were evaluated; linear, linear with plateau, quadratic, and quadratic with plateau. The criteria for model selection were mainly based on the smallest residual sum of squares, but the fitted response curves were also examined to make sure the selected statistical model was reasonable. The economically optimum nitrogen rate (EONR) was calculated assuming the price of corn and N fertilizer to be 98.33 USD·Mg^{-1} and 0.46 USD·kg^{-1} that was representative for the study period, respectively. These data were used to evaluate the potential of using the defined MZs for site-specific N management. More detailed information on this analysis can be found in a separate publication[32].

3 Results

Figures 2–3 illustrate the final MZs delineated by different approaches for each field. They took different forms, demonstrating the need to evaluate the appropriateness of different approaches.

3.1 Soil and landscape variability

The CV values for different soil and landscape properties, and RVs of different MZ delineation approaches are given in Table 1. Relative elevation and slope in both fields were more variable (CV = 44.0%–56.1%) than CEC, EC and OM (CV = 10.7%–30.8%). The three approaches to MZ delineation differed in their ability to account for soil and landscape variability. On average, the ROSE approach explained 53.4% of soil and landscape variability in Field A, followed by the ROSE-YSTTS approach (49.9%). In Field B, the ROSE-YSTTS approach explained the greatest soil and landscape variability (38.5%), followed by the ROSE approach (35.7%). The CMYYM approach explained the least amount of soil and landscape variability in both Field A (38.1%) and Field B (8.9%), as expected.

3.2 Soil nutrient and pH variability

Both fields were high in soil test P and K. The field average soil test P was 35.8 and 48.4 mg·kg^{-1} in Fields A and B, respectively, which were above the critical level of 22.5 mg·kg^{-1}[33]. Average soil test K was 148.9 and 171.9 mg·kg^{-1} in Fields A and B, respectively, which was close to or above the critical level of 150 mg·kg^{-1}. Average soil test S was 9.1 and 9.5 mg·kg^{-1} in Fields A and B, respectively, which was slightly lower than the critical level of 11 mg·kg^{-1}. Average soil test Zn was lower in Field A (1.9 mg·kg^{-1}) than in Field B (3.3 mg·kg^{-1}), and was less than the critical level of 3.5 mg·kg^{-1}[33]. Soil pH was similar in both fields (6.3 and 6.0). In Field A, soil test P was the most variable nutrient (CV = 50.7%), followed by soil test K (CV = 31.4%). CVs of soil S and Zn were 9.1% and 9.9%, respectively. In Field B, soil Zn was the most variable nutrient (CV = 39.1%), followed by soil test

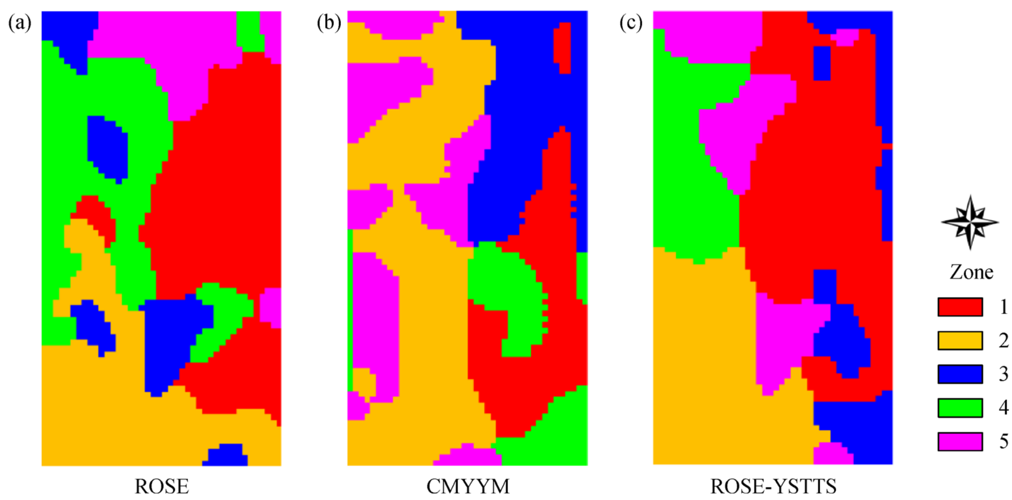

Fig. 2 Management zones delineated with different approaches [ROSE (a); CMYYM (b); ROSE-YSTTS (c)] in Field A

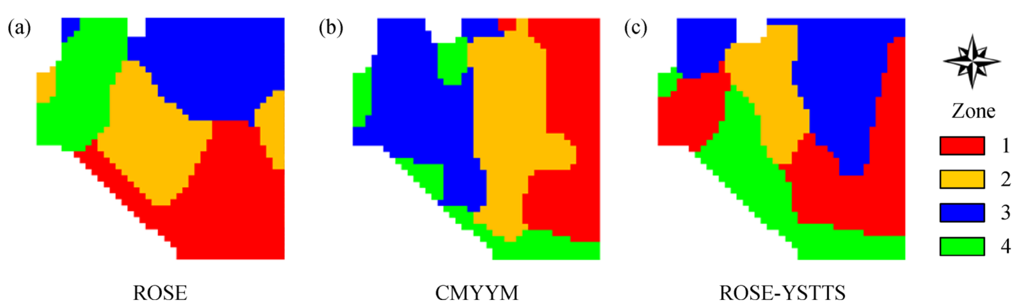

Fig. 3 Management zones delineated with different approaches [ROSE (a); CMYYM (b); ROSE-YSTTS (c)] in Field B

Table 1 Soil and landscape variation from CV and RV as explained by different MZ approaches in Fields A and B (%)

Field	Variability	MZ approach	R-Ele.	Slope	CEC	EC	OM	Average
A	CV		44.0	52.0	23.6	12.6	30.8	
	RV	ROSE	65.2	31.3	62.3	53.7	54.7	53.4
		ROSE-YSTTS	64.9	8.4	55.0	52.0	69.1	49.9
		CMYYM	42.0	6.5	52.8	31.6	57.8	38.1
B	CV		56.1	53.2	19.4	10.7	22.8	
	RV	ROSE	65.7	25.2	20.6	53.5	13.9	35.8
		ROSE-YSTTS	65.9	7.8	38.9	32.2	47.9	38.6
		CMYYM	5.0	21.7	6.3	3.3	8.2	8.9

Note: R-Ele., relative elevation.

P (CV = 33.4%). Soil pH had the lowest variability in both fields (CV = 5.4% and 3.0%) (Table 2).

In general, none of the three approaches explained more than 30% of the variability in soil nutrients (4.4%–26.1%). For pH, the ROSE-YSTTS and CMYYM approaches accounted for more variability in Field A (22.3% and 20.2%, respectively) than the ROSE approach (15.8%). In Field B, the ROSE-YSTTS and ROSE approaches accounted for more variability (52.3% and 39.0%, respectively) than the CMYYM approach (14.2%). On average, the ROSE and ROSE-YSTTS approaches explained a comparable amount of variability in soil nutrients and pH in both fields (15.6% and 16.1% in Field A, 19.7% and 17.3% in Field B, respectively). The CMYYM approach explained less variability in soil nutrients and pH than the other two approaches in both fields, especially in Field B (9.4%), where manure was applied in the past (Table 2).

It should be noted that in Field A, the CMYYM approach (17.1%) accounted for more soil test P variability than the other two approaches (7.9%–8.8%), indicating that yield was more influenced by soil test P in this field than in Field B, where the CMYYM approach (4.4%) accounted for less soil test P variability compared with the other two approaches (5.8%–10.2%). In contrast, soil test K may have influenced crop yield more in Field B than in Field A (Table 2).

3.3 Crop yield variability

Crop yield variability was smaller than soil and landscape variability in the two study fields, with CVs varying from 4.7% to 15.7% in Field A and from 5.3% to 11.7% in Field B (Table 3). Averaged across years, the CMYYM approach accounted for the highest amount of yield variability in both fields (21.8% and 31.2% for Fields A and B, respectively), followed by the ROSE-YSTTS approach (13.2% and 18.7% for Fields A and B, respectively). The ROSE approach accounted for the lowest yield variability in both fields. In some years, the ROSE and ROSE-YSTTS approaches explained similar amounts of yield variability (Table 3).

3.4 Potential for zone-specific nitrogen management

The average EONRs in each MZ in Field B defined using the three delineation approaches are shown in Table 4. Averaged across hybrids and fields, the EONRs were similar in 2001 (174 $kg\cdot hm^{-2}$) and 2003 (176 $kg\cdot hm^{-2}$), which were close to the farm practice (168 $kg\cdot hm^{-2}$). However, EONR varied with different approaches, MZs, hybrids and years. Averaged across the field, the EONR of 33G26 in 2001 (139.7 $kg\cdot hm^{-2}$) was about 68 $kg\cdot hm^{-2}$ less than that of 33J24, while in 2003, the EONRs of these two hybrids were similar. Averaged across years and hybrids,

Table 2 Soil nutrients and pH variation from CV and RV as explained by different MZ approaches in Fields A and B (%)

Field	Variability	MZ approach	P	K	S	Zn	pH	Average
A	CV		50.7	31.4	9.1	9.9	5.4	
	RV	ROSE	7.9	16.9	11.2	26.1	15.8	15.6
		ROSE-YSTTS	8.8	12.4	16.4	20.7	22.3	16.1
		CMYYM	17.1	6.1	11.1	18.1	20.2	14.5
B	CV		33.4	15.4	7.8	39.1	3.0	
	RV	ROSE	10.2	7.1	24.5	17.9	39.0	19.7
		ROSE-YSTTS	5.8	7.0	13.7	7.5	52.3	17.3
		CMYYM	4.4	12.0	15.1	1.5	14.2	9.4

Table 3 Normalized crop yield variation indicated by CV for different years and RV as explained by different MZ approaches in Fields A and B (%)

Field		MZ†	95	97	98	99	00(a)§	00(b)	01	Average
			SB	SB	C	SB	C	C	SB	
A	CV		15.3	15.7	12.3	11.5	4.7	4.8	7.8	
RV	10.3	10.9	12.0	6.0						
		Y	14.2	17.8	20.0	11.4	10.5	1.8	16.7	13.2
		Z	29.7	33.1	24.3	20.2	5.2	16.5	23.7	21.8

Field		MZ	95	96	97	98	99	00	Average
			C	SB	C	SB	C	SB	
B	CV		10.4	11.7	5.3	8.6	7.4	10.2	
	RV	X	23.0	12.3	1.5	9.8	5.6	6.7	9.8
		Y	30.0	25.6	18.3	8.1	22.9	7.3	18.7
		Z	60.0	44.0	25.6	9.7	36.6	11.0	31.2

Note: † MZ delineation approaches X (ROSE), Y (ROSE-YSTTS), and Z (CMYYM); SB, Soybean; C, Corn; § Two hybrids were planted in 2000 in Field A, a (33G26) and b (33Y18).

Table 4 Economically optimum nitrogen rates in MZ for two hybrids defined by different approaches in 2001 and 2003, Field B (kg·hm^{-2})

MZ Approach	MZ	2001		2003		Average	
		33G26	33J24	33G26	33J24	2001	2003
	1	133.3	219.7	178.0	220.9	176.5	199.5
	2	113.4	165.1	159.8	162.0	139.3	160.9
ROSE	3	166.8	229.4	149.6	172.7	198.1	161.2
	4	137.0	238.6	254.4	190.5	187.8	222.5
ROSE-YSTTS	1	127.8	231.2	212.5	255.6	179.5	234.1
	2	116.1	152.4	145.0	155.3	134.3	150.2
	3	174.2	224.5	133.0	158.7	199.4	145.9
	4	129.5	229.6	213.5	173.4	179.6	193.5
	1	165.3	216.5	182.3	223.6	190.9	203.0
CMYYM	2	145.7	233.7	141.3	162.4	189.7	151.9
	3	119.3	183.5	183.5	169.1	151.4	176.3
Field Average		139.7	208.0	169.8	181.3	173.9	175.6

Note: MZ4 not sampled for CMYYM.

the general EONR trend for the ROSE and ROSE-YSTTS approaches followed the same order; MZ1 > MZ4 > MZ3 > MZ2 (Fig. 4). The difference in average EONR between the highest and lowest EONR MZs was larger for the ROSE-YSTTS approach (65 kg·hm^{-2}) compared to the other two approaches (about 55 and 33 kg·hm^{-2}).

Since the ROSE-YSTTS approach was overall more consistent in accounting for the variability in soil, landscape and yield than the other two delineation approaches, it was selected for further evaluation. Compared with uniform N management at 168 kg·hm^{-2}, applying hybrid-, year- and zone-specific N rates delineated using the ROSE-YSTTS approach would increase the economic return from 1.08 to 98.10 USD·hm^{-2} (Fig. 5). In general, MZ1 and MZ4 produced more benefits with hybrid-, year- and MZ-specific N application, while

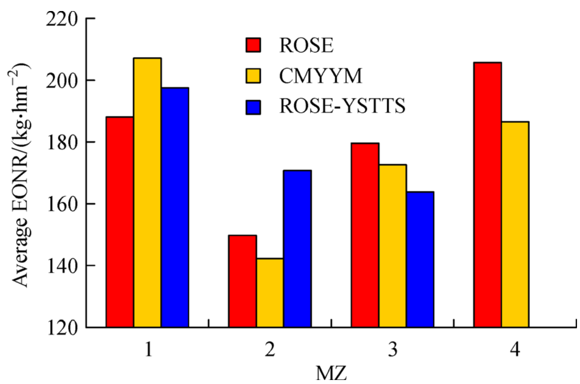

Fig. 4 Average economically optimum nitrogen rates (EONR) across years and hybrids for field B in different management zones defined by ROSE, ROSE-YSTTS and CMYYM approaches.

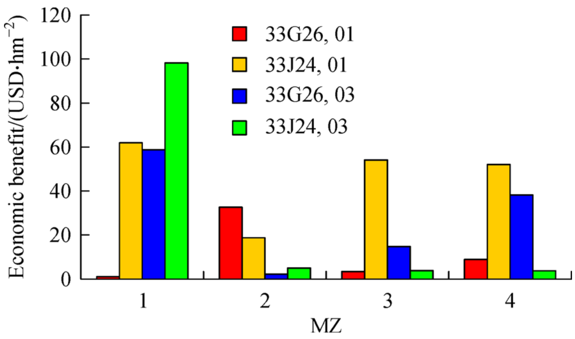

Fig. 5 Profitability of applying hybrid-specific, year-specific, and zone-specific economically optimum nitrogen rates in comparison to a uniform N application rate of 168 kg·hm^{-2} in each zone in 2001 and 2003, Field B.

uniform N application rate would have been acceptable in MZ2 and MZ3, based on two years of data. Averaged across hybrids and years, the economic profit would be 55.21, 14.27, 18.99, and 25.72 USD·hm^{-2} higher than with uniform N management in zones 1, 2, 3 and 4, respectively.

4 Discussion

4.1 Integrated approach to site-specific management zone delineation

When a farmer wants to adopt precision agriculture, the first step is probably to divide a field into a few relatively uniform MZs. This is a practical and cost-effective, site-specific management approach with current technology and price relationships, although zone management may not be the best choice in the long run with development of crop and soil sensors and availability of other high spatial density data. Different MZ delineation approaches have been proposed, and it is natural to ask which approach should a farmer adopt and how to evaluate different MZ delineation approaches or the delineated MZs. At least three different criteria have been used to assess site-specific nutrient management zones: (1) soil nutrient variability minimization, (2) yield variability minimization, and (3) fertilizer recommendation error minimization[29]. The defined MZs should have relatively uniform inherent soil fertility (soil OM and CEC), landscape properties that affect soil water variability, hydrological conditions and crop yield potential, and yield variability[34,35]. To be useful in precision N management, each zone should have similar N requirement or EONR, and different MZs should have different optimum N rates.

One of the objectives of most crop management systems is to optimize crop yield, therefore crop yield is the most important property that should be included in MZ delineation. Temporal crop yield variability is affected primarily by weather and genetics (cultivar change), while spatial variability is affected primarily by soil and landscape properties, management practices (e.g., planting densities and date, and fertilizer rate and timing), stresses, pests and their dynamic interactions. As a result, MZs defined only with soil and landscape information may not be able to account for much of the temporal variability in yield, especially when a field had been historically managed as more than one field, as in this study. Similarly, MZs defined only with yield information may not account for much of the spatial variability in soil or landscape properties. Many years of yield maps may be needed to fully characterize the spatial and temporal patterns in crop yield. It was suggested that five to ten years of yield maps are required[27,36]. These yield maps should be normalized and spatial yield pattern maps and temporal stability maps should be created and used in the MZ delineation procedure[24].

The results of this study indicated that the integrated ROSE-YSTTS strategy combining both soil and landscape properties and spatiotemporal yield variability information could overcome the weaknesses of approaches using either source of information alone. It may not be the best approach in explaining either soil and landscape properties or yield variability but it is the overall best approach in explaining both sources of variability and should be more stable across different environments. More studies are needed to further evaluate this integrated approach in more fields to determine whether this approach can be effectively applied to other fields.

A challenge to using the integrated ROSE-YSTTS approach proposed in this study is that many farmers will not have multi-year yield maps, especially in developing countries. In this case, multiple remote sensing images taken during the growing season over the past several years may be used to estimate the spatial and temporal patterns in yield, which can then be used for MZ delineation as demonstrated for cotton[37] and rice[38].The approach combining high resolution satellite remote sensing images and crop growth model simulations for creating yield maps without the need for any ground measured yield data are especially promising for fields without yield monitoring data[39–41].

Another challenge is to obtain a soil OM map. This can be estimated using remote sensing images[20,42], on-the-go soil sensors[43] or active crop sensors[44]. Considering the relationships between soil OM with soil EC or terrain attributes[43,45], soil OM information may not be needed, which should be further evaluated. The suitable combination of factors for MZ delineation may be field-specific, depending on the field variability situation.

Since EC is not only related to stable soil properties like OM, cation exchange capacity, soil texture, depth of topsoil above clay-pans, but also to dynamic properties like soil moisture and soil ionic concentration[46], its temporal stability needs to be considered. It has been reported that when salt concentration and buildup are low, single EC mapping should be fine for MZ delineation in irrigated sandy fields[47]. However, another study indicated that the temporal stability of soil EC differed with soil types, with greater temporal stability in Acrisol and Cambisol soils distributed in upper slope areas, but low temporal stability in Gleysol and Nitosol soils distributed in areas of low elevation, thick soil solum and fluctuated water table[48]. More studies are needed to further evaluate the temporal stability of EC and implications for site-specific MZ delineation.

The results of this study indicated that none of the MZ approaches performed well in accounting for soil nutrient variability, with the average RVs being less than 20%. Perhaps this was because soil nutrient variability was not that important in producing spatial and temporal variability in crop yield for these fields during the study period and other factors, such as soil moisture, may be more important. In addition to the influence of soil and landscape factors, spatial soil nutrient patterns can be strongly affected by fertility management, including manure application or other organic fertilizer application, rotation, fertilizer application (what, when, how, where and frequency). As a result, their spatial patterns may or may not be related to spatial patterns of soil and landscape properties, or yield.

4.2 Strategies for zone-specific nitrogen management

After the MZs are successfully defined, the greatest challenge facing the producer is how to manage them to optimize profit and/or reduce environmental contamination. The potential limiting factors in each zone need to be diagnosed and corrective measures taken to manage them accordingly. In this study, MZ1 and MZ2 defined by the ROSE-YSTTS approach in Field B were found to have higher and lower average EONR than other zones, and MZ-, hybrid- and year-specific N management could increase an average of 14.27–55.21 USD·hm^{-2} profits compared with uniform application of 168 kg·hm^{-2} N fertilizers. This only represented the potential of precision N management. The challenge is how to determine the MZ-, hybrid- and year-specific EONRs in advance. The uncertainty of weather conditions in the next growing season poses the same challenge to site-specific management as to uniform management on a whole field basis. The EONRs may not be consistent in other years, particularly if weather, hybrid or management practices change.

Process-oriented crop growth models can simulate crop growth, development and yield based on the interactions of genetics, weather, soil conditions and management and have been used to identify yield limiting factors and corresponding yield losses, evaluate management prescriptions and forecast spatial yield patterns[49]. Using crop growth models to determine optimum N rates in each MZ may be a viable and practical option for site-specific N management[15]. A modified version of the CERES-Maize model was used to estimate optimal N rates for different MZs in Field B using 15 years of weather data and the results indicated that MZ-, hybrid- and year-specific N management had the potential to increase net return by an average of about 50 USD·hm^{-2} compared with uniform N application of 170 kg·hm^{-2}[15]. However, if the average MZ- and hybrid-specific RONRs were applied across years, no consistent improvement in economic returns over uniform N application was found[15]. This result indicated that year-to-year weather variability needs to be considered in MZ-specific N management. A more promising approach is probably to use crop growth models to determine MZ- and cultivar-specific N rates based on long-term simulation, and then apply a moderate amount at or before planting. During the growing season, active canopy sensors[50–52], unmanned aerial vehicle remote sensing[53] or satellite remote sensing[12,54] can be used to nondestructively diagnosis crop N status and fine-tune in-season top- or side-dressing N application rates. Such strategies need to be evaluated to improve and facilitate MZ-based precision nutrient management.

5 Conclusions

This study evaluated three approaches to defining site-specific management zones on two no-till corn-soybean rotation fields. The results indicated that in general, the ROSE approach using only soil and landscape information was least effective in accounting for crop yield variability, while the CMYYM approach using only multi-year yield maps was least effective in accounting for soil and landscape, and soil nutrient variability. The integrated ROSE-YSTTS approach combining soil, landscape and yield spatial trend and temporal stability information was reasonably effective and more consistent in accounting for these three sources of variability. It was also found that in Field B where two years of N rate experiment data were available, the ROSE-YSTTS approach was effective in separating zones into high (MZ1), medium (MZ3 and MZ4) and low (MZ2) economically optimum N rate zones. Averaged across hybrids and years, applying hybrid-, year- and zone-specific economically optimum N rates had the potential to increase economic return by 55.21, 14.27, 18.99 and 25.72 USD·hm^{-2} over a uniform N application rate of 168 kg·hm^{-2} in zones 1, 2, 3 and 4, respectively. It is concluded that the ROSE-YSTTS approach combining soil, landscape and yield spatiotemporal variability information can overcome the weaknesses of approaches using only soil, landscape or yield information, and is more robust. It also has the potential for site-specific N management for improved economic returns. More studies are needed to further evaluate their appropriateness for precision N and crop management.

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