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Appropriateness of Management Zones for Characterizing Spatial Variability of Soil Properties and Irrigated Corn Yields across Years

Aaron R. Schepers, John F. Shanahan,* Mark A. Liebig, James S. Schepers, Sven H. Johnson, and Ariovaldo Luchiari, Jr.

ABSTRACT

Recent precision-agriculture research has focused on use of management zones (MZ) as a method for variable application of inputs like N. The objectives of this study were to determine (i) if landscape attributes could be aggregated into MZ that characterize spatial variation in soil chemical properties and corn yields and (ii) if temporal variability affects expression of yield spatial variability. This work was conducted on an irrigated cornfield near Gibbon, NE. Five landscape attributes, including a soil brightness image (red, green, and blue bands), elevation, and apparent electrical conductivity, were acquired for the field. A georeferenced soil-sampling scheme was used to determine soil chemical properties (soil pH, electrical conductivity, P, and organic matter). Georeferenced yield monitor data were collected for five (1997–2001) seasons. The five landscape attributes were aggregated into four MZ using principal-component analysis of landscape attributes and unsupervised classification of principal-component scores. All of the soil chemical properties differed among the four MZ. While yields were observed to differ by up to 25% between the highest- and lowest-yielding MZ in three of five seasons, receiving average precipitation, less-pronounced (≤5%) differences were noted among the same MZ in the driest and wettest seasons. This illustrates the significant role temporal variability plays in altering yield spatial variability, even under irrigation. Use of MZ for variable application of inputs like N would only have been appropriate for this field in three out of the five seasons, seriously restricting the use of this approach under variable environmental conditions.

Recent research in precision agriculture has focused on use of MZ as a method to more efficiently apply crop inputs such as N across variable agricultural landscapes (Franzen et al., 2002; Ferguson et al., 2003). Management zones, in the context of precision agriculture, are field areas possessing homogenous attributes in landscape and soil condition. When homogenous in a specific area, these attributes should lead to the same results in crop yield potential, input use efficiency, and environmental impact.

Approaches to delineate MZ vary. Topography has been suggested as a logical basis to define homogenous zones in agricultural fields (Franzen et al., 2002). This approach has been applied in Illinois and Indiana where 40% of grain yield variability was explained by topographical characteristics and selected soil properties (Kravchenko and Bullock, 2000). Aerial photographs, crop canopy images, and yield maps have also been suggested as approaches to delineate MZ (Schepers et al., 2000). Remote sensing technology is especially appealing to identify MZ because it is noninvasive and low in cost (Mulla and Schepers, 1997). Additionally, scientific evidence for suggesting practical use of remote sensing technology to delineate MZ is increasing (Varvel et al., 1999).

Another promising noninvasive approach to define the boundaries of MZ involves the use of electromagnetic induction to measure apparent electrical conductivity (EC_a). This approach has been used to effectively map variations in surface soil properties such as salinity, water content, and percentage clay (Corwin and Lesch, 2003; Kitchen et al., 2003). In a semiarid cropping system, Johnson et al. (2003) showed that EC_a–determined MZ could be used to characterize spatial variation in wheat (*Triticum aestivum* L.) and corn (*Zea mays* L.) yields. Magnetic induction has also been used to track soluble nutrient levels in soil (Eigenberg et al., 2002). Caution is necessary when using this approach because of the extreme sensitivity to soil type and management conditions, but its ease of use makes it an attractive tool for precision farming applications (Lund et al., 1998).

Yield mapping is yet another approach to delineate MZ. This approach is considered to be the primary form of precision-agriculture technology in the USA (Pierce and Nowak, 1999). However, practical application of yield mapping to identify zones has been plagued by spatial and temporal variation in measured yield (Huggins and Alderfer, 1995; Sadler et al., 1995). Consequently, most efforts in yield map interpretation have focused on identifying generalized zones of low, medium, and high yield (Stafford et al., 1998).

While using MZ to characterize spatial variability in soil and crop properties is important in site-specific studies, it is equally important to consider the temporal effects of climate variability on expression of spatial variation in crop yields. For example, Eghball and Varvel (1997) and Lamb et al. (1997) found under rainfed conditions that temporal variability of corn yields was more dominant than spatial variability, indicating that spatial patterns in grain yields were greatly affected by yearly

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Abbreviations: CV, coefficient of variation; DGPS, differential global positioning system; DN, digital number; EC, electrical conductivity; EC_a, apparent electrical conductivity; GIS, geographical information systems; MZ, management zones; OM, organic matter; PC, principal component; PCA, principal-component analysis.

variations in climate, particularly by year-to year changes in seasonal water supply. Since the previous work was conducted under rainfed conditions, we were interested in determining if climate variability has similar effects on spatial patterns of irrigated corn yields where temporal variations in seasonal water supply are typically less than under rainfed conditions. For farming by MZ to be effective, it is necessary to demonstrate a strong and consistent relationship between spatial patterns in soil properties used to delineate MZ and spatial patterns in crop yields over yearly variations in climate. Otherwise, the variable application of crop inputs like N, based on soil-derived MZ alone, will likely be done incorrectly. The objectives of this study were to determine under irrigated conditions (i) if landscape attributes such as soil brightness, elevation, and EC_a could be aggregated into MZ that characterize spatial variation in soil chemical properties as well as corn yields and (ii) if temporal variability affects expression of yield spatial variability.

MATERIALS AND METHODS

Site Description and Crop Management

The study was conducted on a 51-ha center-pivot–irrigated cornfield (Fig. 1) located near Gibbon, NE (40°53’27 N, 98°51’37 W; 640 m above mean sea level). The topography is rolling, with approximately 24 m of relief. The Hobbs and Uly soil series are present in this field (USDA Soil Conserv. Serv., 1974), and their map symbols and boundaries are depicted in Fig. 1. The Hobbs soil series (2HB) were formed in water-deposited silts and consist of deep, medium-textured, well-drained, nearly level to gently sloping soils present at the base of slopes, on alluvial fans, and on bottomlands. Consequently,

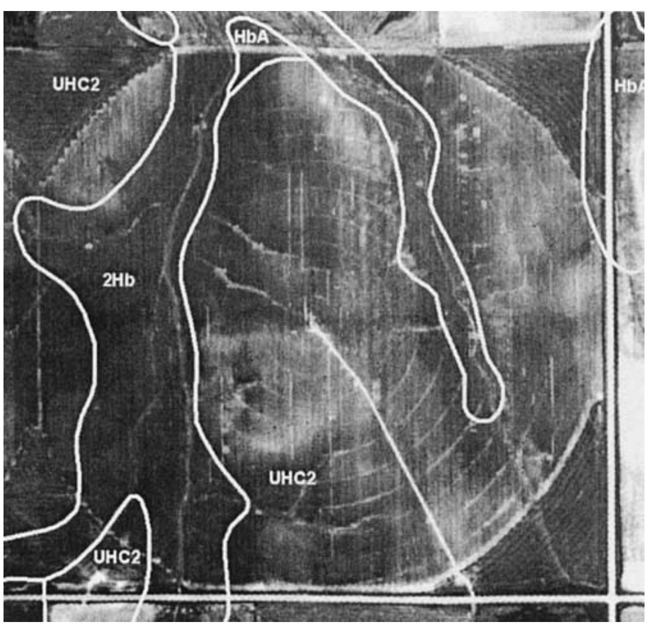

Fig. 1. Bare soil aerial image of Gibbon, NE, corn study site acquired in spring of 1999. Map symbols and boundaries are depicted for the Hobbs (2Hb) and Uly (HbA and UHC2) soil series, which are present in this field (USDA Soil Conserv. Serv., 1974). The Hobbs series consists of deep, medium-textured, well-drained, nearly level to gently sloping soils formed in water-deposited silts while the Uly series consists of deep, well-drained, medium-textured, moderately to strongly sloping soils formed in calcareous loess.

they are occasionally flooded, receiving runoff from adjacent hills. The Uly series (HbA and UHC2) consist of deep, well-drained, medium-textured, moderately to strongly sloping soils formed in calcareous light brownish-gray loess of 1.5 m in depth or more. When not flooded, the Hobbs soil series are considered more productive soils than the Uly series (USDA Soil Conserv. Serv., 1974).

The field was managed and operated by the same farmer cooperator throughout the course of this study. The field has been planted continuously to corn since 1990, using ridge till methods. Best management practices, regarding crop nutrients, irrigation water application, and pest control, were utilized each growing season to maximize yields and economic returns. Rainfall amounts and other climatic data for each growing season were recorded by the High Plains Climate Center Network (University of Nebraska) through the use of an automated weather station located 5 km south and east of the study area.

Acquisition of Spatial Data Layers

The spatial data layers collected for this study site included a bare soil brightness image (red, green, and blue color bands), elevation, EC_a, and crop yield for each growing season using a yield-mapping combine. All elevation, EC_a, and crop yield data were georeferenced with a differentially corrected Trimble Model 114 differential global positioning system (DGPS) receiver (Trimble Navigation, Sunnyvale, CA) with submeter accuracy. Spatial coordinates for all data were projected to Universal Transverse Mercator (UTM), Datum GRS80, Spheroid NAD83, and Zone 14. The geographical information system (GIS) package used to manipulate the spatial data was ERDAS Imagine (ERDAS, Atlanta, GA).

Bare soil brightness was determined by acquiring an aerial image of the field in the early spring of 1999 when minimal crop residue was present on the surface. An aircraft flying at an approximate elevation of 2133 m and equipped with a belly mounted 35-mm camera and Kodak Ektachrome color film was used to acquire the image. The image was scanned at 1200 dpi and imported into the GIS. Georeferencing was performed through an image-to-image technique using a Digital Orthophoto Quadrangle (DOQ). The bare soil aerial image, which originally had a nominal ground resolution of about 0.5 m, was resampled to 5-m spatial resolution. Soil brightness was expressed as reflectance intensity (digital number) in the red, green, and blue spectral bands of the digitized image.

The entire field site was EC_a–mapped in the early spring of 1999, using an electromagnetic induction EM-38 ground conductivity sensor (Geonics Ltd, Mississauga, ON, Canada). The sensor uses electromagnetic energy to measure the apparent conductivity of earthen materials. The sensor was mounted on a nonmetallic cart 0.36 m above the soil surface and pulled at a speed of 16 km h^{-1} through the field with a truck following parallel swaths (18-m intervals), requiring around 2 h to EC_a–map the entire field. The sensor was operated in the vertical mode, which measured an effective soil layer of 0 to 1 m. Conductivity data were logged at 1-s intervals and georeferenced using the Trimble DGPS receiver mounted near the EM-38 sensor. Elevation data obtained from the DGPS receiver during EC_a mapping were used for determination of relative elevation. Although the DGPS receiver used in our work provided elevation data of only 1- to 2-m accuracy, the increased precision of real-time kinematic (RTK) receiver (centimeter accuracy) was considered unnecessary since this field possessed around 24 m of relief and it was not necessary to resolve small differences in elevation.

Before planting of the 1999 crop, an arbitrarily designed and georeferenced soil-sampling scheme was used to assess soil chemical properties [pH, electrical conductivity (EC), P, and organic matter (OM)] known to affect crop yield. Within a 10-m radius of each sampling point, 20 soil cores were collected to a 0.30-m depth and composited. Soil samples were analyzed for pH, EC (1:1 soil/water ratio), extractable P (sodium bicarbonate extraction), and soil OM (estimated from soil organic C). Total C was determined using the Dumas dry combustion technique (Schepers et al., 1989).

Crop yields were mapped for five consecutive seasons (1997–2001) with a John Deere 9600 combine (12-row corn head) equipped with a GreenStar yield-monitoring system and DGPS receiver. The yield monitor was calibrated each year to weight wagon estimates. Data for grain yield, moisture, and geocoordinates were recorded every second. Yield data were processed and mapped with Farm HMS software version 2.1 (Red Hen Syst., Fort Collins, CO) to minimize errors due to combine grain flow dynamics, sensor offsets, and DGPS antenna placement. Additionally, short map segments associated with field entry, loss of DGPS signal, and data points outside ±3 standard deviations of the field average were removed. After yield map and error processing, approximately 5600 to 5800 yield points were retained in the yield maps for each season.

Management Zone Delineation

To represent the spatially less dense elevation and EC_a data on the same spatial resolution as soil brightness (5 m), elevation and EC_a point data were interpolated into surfaces with 5-m grids using kriging techniques available in GS+ (Gamma Design Software, Plainwell, MI) version 3.1. First, the extent of spatial dependency of the data was determined with the Moran's I statistic. The Moran's I statistic is a conventional measure of spatial autocorrelation, similar in interpretation to the Pearson's Product Moment correlation statistic for independent samples in that both statistics range between −1.0 and 1.0, depending on the degree and direction of correlation. The Moran's I statistic is defined as: $I(h) = N(h) \Sigma \Sigma z_i z_j / \Sigma z_i^2$, where $I(h)$ = autocorrelation for interval distance class h, z_i = the measured sample value at point i, z_j = the measured sample value at point $i + h$, and $N(h)$ = total number of sample couples for the lag interval h.

If spatial autocorrelation was observed, semivariance analysis was conducted to determine the type of spatial structure present for each variable. Semivariance is an autocorrelation statistic defined as: $\gamma(h) = [1/2N(h)] \Sigma (z_i - z_i + h)^2$, where $\gamma(h)$ = semivariance for interval distance class h, z_i = measured sample value at point i, $z_i + h$ = measured sample value at point $i + h$, and $N(h)$ = total number of sample couples for the lag interval h. Five variogram models (spherical, exponential, linear, linear to sill, and gaussian) and model parameters (nugget, sill, and range) were evaluated to determine which best fit the spatial structure of each variable. The program uses the coefficient of determination (R^2) and reduced sums of squares (RSS) to select the best models and model parameters that maximize R^2 and minimize RSS values. Variogram models were also evaluated for presence of anisotropy (direction-dependent trend in the data) and adjusted accordingly. Data were then block-kriged using the appropriate variogram models to produce interpolated maps with 5-m grids for each variable. Finally, cross-validation analysis was conducted as a means for evaluating alternative models for kriging. In cross-validation analysis, each measured point in a spatial domain is individually removed from the domain and estimated via kriging as though it were never there. In this way, a comparison can be made of estimated vs. actual values for each sample location in the domain and coefficients of determination used to assess goodness of fit of the modeled surface. The kriged surfaces for elevation and EC_a, generated in GS+, were then imported into the GIS to complement the three spectral bands of the bare soil image.

To summarize and delineate the five landscape attributes into MZ, normalized principal-component analysis (PCA) was performed on these five variables in ERDAS. Principal components for a data set are defined as linear combinations of variables that account for the maximum variance within the entire data set by describing vectors of closest fit to the n observations in p-dimensional space, subject to being orthogonal to one another. A correlation matrix involving the five landscape attributes was used as input for the analysis in lieu of a covariance matrix, resulting in normalized PCA. There are many documented strategies for using PCA or closely related factor analyses to select a smaller subset of variables from a larger number of variables. The strategy we utilized is similar to that described by Dunteman (1989). We assumed that principal components (PCs) receiving high eigenvalues best represented the landscape attributes. Therefore, we retained only the PCs with eigenvalues greater than 1. Unsupervised classification was then performed, using values for the retained PCs, to develop four management zone classes, with 95% convergence of class membership after a maximum of six iterations.

Unsupervised classification identifies statistically similar clusters, and as a result, the classified map may contain relatively small clusters of one zone interspersed among other zones. To minimize the occurrence of these small-interspersed clusters, a 1.25-ha moving majority filter was applied to the data to aggregate MZ, resulting in a more homogeneous set of manageable zones. The majority filter operates by replacing the value in the center of the 9- by 9-pixel window (1.25 ha) with the most frequently occurring MZ number. The pixel window size is determined by the spatial resolution of the data set, which for this data set was 5 m.

To assess whether our method of utilizing landscape attributes to delineate MZ could be used to characterize spatial variation in soil chemical properties and crop productivity, all georeferenced soil sample and yield data points for each growing season were assigned to one of the four respective MZ in the GIS. Once soil sample and yield data points were assigned zone classification, the data were exported and analyzed via analysis of variance using a mixed model with SAS PROC MIXED procedure (Littel et al., 1996). For the soil properties, MZ were considered fixed effects and samples within each zone as repeated observations. For yield data, the analysis was modified slightly, adding a spatial component to the mixed model by using the spatial option in the repeated statement of PROC MIXED to describe the spatial structure for yield variability. This was accomplished by first determining the most appropriate spatial model and model parameters (nugget, sill, and range) best describing the spatial structure of yield variability for each year using the GS+ program and the previously described procedures. The variogram model parameters determined for each year served in turn as input in the spatial option in the repeated statement of the PROC MIXED model analyses used to compute the F test for MZ effects on crop yields. The Akaike's information criterion (AIC) was used as a means for selecting the best spatial component for the mixed-models analyses (Bozdogan, 1987). In all seasons, the inclusion of the appropriate variogram model and model parameters as spatial components in the analyses reduced the AIC values, compared with a standard analysis with no spatial component, thus improving the accuracy of the F test comparing MZ effects on yield.

Table 1. Statistics of the five landscape attributes acquired at the Gibbon, NE, corn study site consisting of red, green, and blue bands of soil brightness image [digital number (DN) for each band]; elevation; and apparent electrical conductivity (EC_a).

	Bands of soil brightness image				
Statistics	Red	Green	Blue	Elevation	EC_a
	DN			m	dS m^{-1}
n	20 464	20 464	20 464	9 577	9 577
Mean	149	132	124	654.7	0.324
Minimum	100	90	58	645.9	0.175
Maximum	243	235	243	670.0	0.501
SD	16	16	21	5.8	0.035
CV, %	10.5	11.9	17.0	0.9	11.0

RESULTS AND DISCUSSION

The aerial image acquired in early spring (Fig. 1) revealed considerable variation in soil brightness, expressed as digital numbers (DNs) for red, green, and blue spectral bands of the image, with coefficients of variation (CVs) for the three bands ranging between 10 and 17% (Table 1). Likewise, we observed substantial variability in topography, with elevation varying by 24 m across the site. The EC_a survey of the landscape also revealed significant variation in this attribute, with a CV of 11%.

We observed considerable spatial variation in grain yields for each growing season (Table 2), with CVs varying from a low of 8.7% to a high of 13%. Likewise, we observed substantial variability in season-to-season average yields, ranging from a low of 10.3 Mg ha^{-1} for 1999 to a high of 12.9 Mg ha^{-1} for 2001, representing a difference of 25%. Thus, we observed not only significant within-field spatial variability, but also significant temporal variability in grain yield. The temporal variability in grain yields was likely due to the marked differences in total growing season precipitation among years, with the driest (2000) and wettest (1999) seasons receiving 62 and 124% of average precipitation, respectively (Table 2). The dry and wet conditions also reduced the spatial variability in yield as the 1999 and 2000 seasons produced the lowest-yield CVs of the 5 yr (Table 2). In summary, our measurements of both landscape attributes and crop yields across growing seasons appear to show adequate spatial variability in soil properties as well as spatial and temporal variability in crop yields to address our study objectives.

The variation for both elevation and EC_a was spatially dependent as determined by the Moran's I test (data not shown), providing justification for semivariance analysis and block kriging to produce kriged surfaces of these two variables. The coefficients of determination for cross-validation analysis of the elevation and EC_a surfaces were 0.987 and 0.888, respectively, indicating that the kriged surfaces fit the raw data reasonably well.

Table 2. Corn yield statistics for 5 yr and May–September precipitation at the Gibbon, NE, corn study site.

Year	*n*	Mean	Minimum	Maximum	SD	CV	May–Sept. precipitation
		Mg ha^{-1}				%	mm
1997	5686	11.3	6.8	15.9	1.5	13.3	360
1998	5810	12.0	7.7	16.4	1.4	11.7	460
1999	5661	10.3	7.7	13.0	0.9	8.7	520
2000	5845	11.4	8.3	14.5	1.0	8.8	260
2001	5670	12.9	9.4	16.3	1.2	9.3	420
5-yr avg.	5734	11.6	8.0	15.2	1.2	10.4	420†

† Represents the 50-yr average precipitation for the location.

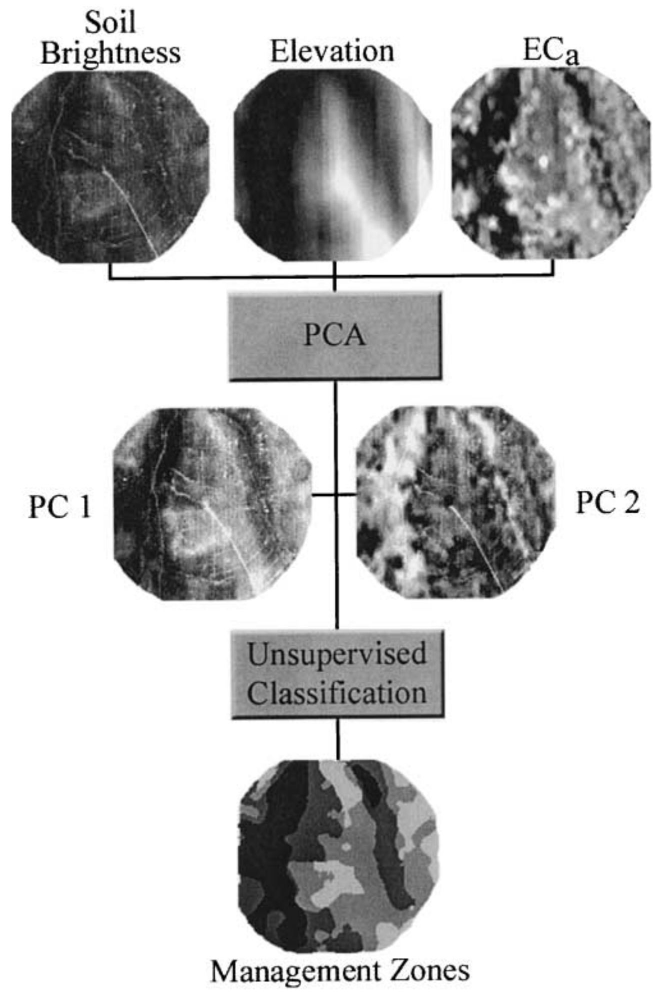

Fig. 2. (Top) Gray-scale maps of five landscape attributes acquired at the Gibbon, NE, corn study site consisting of red, green, and blue bands (shown in one map) of soil brightness image, elevation, and apparent electrical conductivity (EC_a), with variations in color, from dark to light, corresponding to increasing values for all landscape attributes. (Middle) Gray-scale maps of principal-component (PC) scores for PCs 1 and 2, resulting from principal-component analysis (PCA) of five landscape attributes, with variations in color, from dark to light, corresponding to decreasing PC scores. (Bottom) Gray-scale map of management zones (MZ), resulting from unsupervised classification of PC scores for two PCs, with variations in color, from dark to light, corresponding to MZ 1 through 4.

The surfaces for elevation and EC_a, along with the soil brightness image (Fig. 2), depict distinct spatial patterns for the five landscape attributes, and the spatial patterns among variables were associated as indicated by the positive correlations among grid values for all landscape attributes (Table 3). For example, the lighter-colored soils (higher DN values) were associated with higher elevations and sites of greater erosion while the darker-colored soils (lower DN values) were associated with lower regions of the field where erosional deposition occurred. Likewise, the EC_a map revealed patterns similar to elevation and soil brightness maps, with low

Table 3. Linear correlation matrix of the five landscape attributes acquired at the Gibbon, NE, corn study site, consisting of red, green, and blue bands of bare-soil brightness image; elevation; and apparent electrical conductivity (EC_a).†

	Red	Green	Blue	Elevation	EC_a
Red	1.00				
Green	0.96	1.00			
Blue	0.77	0.83	1.00		
Elevation	0.52	0.52	0.46	1.00	
EC_a	0.35	0.34	0.28	0.39	1.00

† Correlation values of 0.062 and 0.081 are significant at the 0.05 and 0.01 levels, respectively.

EC_a values observed for the lowland, dark-colored areas and higher EC_a values found for the light-colored, more eroded, upland regions (Table 3 and Fig. 2). These positive associations among elevation and the other independently measured soil attributes (soil brightness and EC_a) indicate that the DGPS receiver used in our work apparently provided accurate measurements of relative elevation differences across this field. If elevation measurements were inaccurate, one would not expect any associations among spatial patterns in elevation and the other landscape attributes. Thus, it was not necessary at this site to use a more accurate GPS receiver to capture the relative elevation features of this field, given the significant range in elevation (Table 1).

To aggregate and summarize the variability in the five landscape attributes, standardized PCA was performed, retaining PCs producing eigenvalues greater than 1. Using these criteria, only the first two PCs were considered for the final analysis, with the two PCs accounting for 85% of the variability in the five landscape attributes (Table 4). The PC loading values for the two PCs shown in Table 4 indicated the elevation, and EC_a variables had the most significant influence on PC 1 although their influence was opposite in direction as indicated by their positive and negative signs. Regarding the soil brightness information, loadings for PC 1 indicate the green and red bands had more influence on PC 1 than the blue band. Thus, it appears that the green band may be slightly more useful than the red and considerably more useful than the blue band in delineating soil brightness conditions. For PC 2, the EC_a variable again produced a large loading value relative to the other variables. In summary, the PCA aggregated the five landscape attributes into two PCs, accounting for a majority of the overall spatial variability in these attributes.

To classify these two PCs into MZ, PC scores for the first two PCs were layer-stacked into the GIS where unsupervised classification was performed. The resultant MZ map, depicting four MZ, is shown in Fig. 2. This map illustrates that the procedures utilized for aggregating landscape attributes resulted in a MZ map with spatial patterns very similar to those of the landscape attributes. For example, MZ 1 and 4 portray the extremes of the dark- and light-colored soils, respectively, and the other two zones represent transitions between the two extremes. According to the soil survey classification map, MZ 1 appears to be located primarily in the region of the highly productive Hobbs soil series

Table 4. Principal-component (PC) analysis of the five landscape attributes acquired at the Gibbon, NE, corn study site consisting of red, green, and blue bands of bare-soil brightness image, elevation, and apparent electrical conductivity (EC_a).

PC	Component loading	Cumulative loading
	%	%
PC 1	60.3	60.3
PC 2	24.8	85.1
PC 3	10.5	95.6
PC 4	3.7	99.2
PC 5	0.6	99.8
PC 6	0.2	100.0

PC	PC loadings for each variable				
	Red	Green	Blue	Elevation	EC_a
PC 1	0.82	1.00	−0.55	1.26	−1.19
PC 2	0.44	0.53	−0.29	0.20	1.40

while the other three zones were situated in the less-productive Uly series (Fig. 1).

One of our research objectives was to determine if landscape attributes could be aggregated into MZ that characterize spatial variation in soil chemical properties affecting crop productivity. The georeferenced sampling scheme utilized for acquiring soil samples for analyses (pH, EC, P, and OM), and its distribution across the four MZ, is depicted in Fig. 3. The results from the soil-sampling analyses revealed distinctly different soil chemical properties for the four MZ (Table 5). For example, we detected a nearly 50% increase in OM levels from the light-colored and upland soils of MZ 4 to the darker-colored, lowland soils of MZ 1, implying a negative association between soil brightness and OM, which is similar to the results of Varvel et al. (1999), who also found a negative association between these two variables for other Nebraska soils. For pH and EC, soil test values increased with increasing elevation while for soil P, the opposite trend was observed (Table 5). Since calcareous subsoil is present at this site (Fig.1), eroded areas would be expected to have higher carbon-

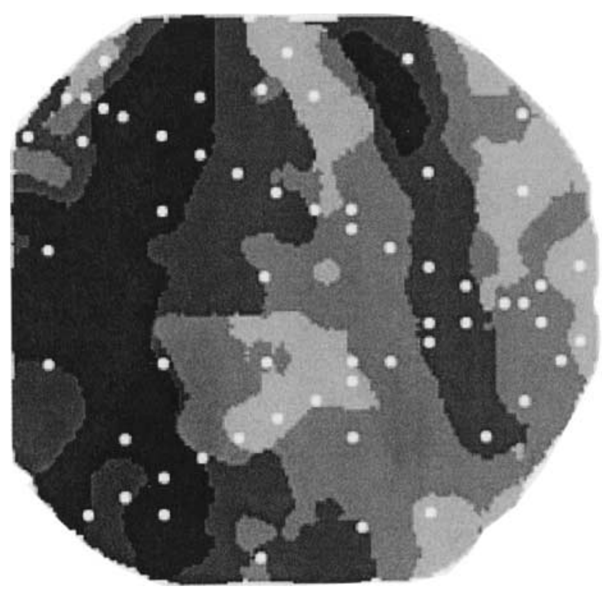

Fig. 3. Georeferenced soil-sampling scheme used to assess soil chemical properties at the Gibbon, NE, corn study site overlain on to the management zones (MZ) map. Variations in color, from dark to light, correspond to MZ 1 through 4.

Table 5. Soil pH, electrical conductivity (EC), P, and organic matter (OM) measured in the 0.3-m depth at the Gibbon, NE, corn study site in the four management zones (MZ).

		Soil attribute			
MZ	*n*	pH	EC	P	OM
			dS m^{-1}	kg P ha^{-1}	g kg^{-1}
1	12	6.41	0.28	71.7	14.2
2	16	6.48	0.30	35.9	13.8
3	19	6.64	0.33	20.1	11.5
4	12	7.43	0.42	9.4	9.5
				ANOVA	
Source	df			$P > F$	
MZ	3	<0.0001	0.0002	<0.0001	0.0318

ate levels, resulting in higher pH and EC values and reduced available soil P. In summary, soil chemical properties were much more optimal for crop growth in the dark-colored soils of MZ 1 than in the lighter-colored soils of MZ 4. Our results agree with those of Kravchenko and Bullock (2000) regarding the association among soil properties such as pH, EC, P, and elevation. Thus, it appears that landscape attributes such as soil brightness, elevation, and EC_a can be used to delineate MZ that characterize spatial variation in soil chemical properties.

Subsequent to demonstrating the value of using MZ for characterizing soil chemical properties, we were also interested in confirming if this same approach could be used to characterize the spatial variability of grain yields across variable climatic conditions. The georeferenced yield maps depicted in Fig. 4 indicate that temporal variability alters the pattern of yield spatial variability expressed in a given year. For example, in 1997, 1998, and 2001, years with average precipitation (Table 2), we observed distinct spatial patterns for grain yields, which resembled spatial patterns of the MZ map (Fig. 4), with highest yields located in MZ 1 and lower yields in MZ 3 or 4. Conversely, in 1999 and 2000, the yield spatial patterns were less distinct, differed from the other 3 yr (Fig. 4), and did not resemble the MZ map (Fig. 3). The variogram models (Fig. 5) along with the appropriate model parameters (nugget, sill, and range) determined from the semivariance analysis (Table 6) also illustrate that the spatial structure of yield variability differed among years. For example, we observed much smaller range values, the separation distance when yields are no longer spatially correlated, for the 1999 and 2000 variogram models vs. the other 3 yr. Thus, spatial dependency of yields extended much further in 1997, 1998, and 2001 than in 1999 and 2000. Again, this is can be seen in the yield maps (Fig. 4) where similar yields were observed to extend for greater distances in 1997, 1998, and 2001, producing yield patterns more

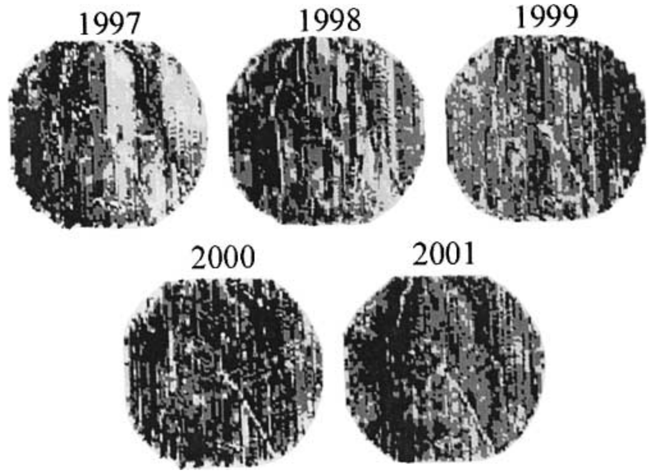

Fig. 4. Gray-scale yield maps of the 1997 through 2001 crop seasons from the Gibbon, NE, site. Variations in color, from dark to light, correspond to decreasing grain yields.

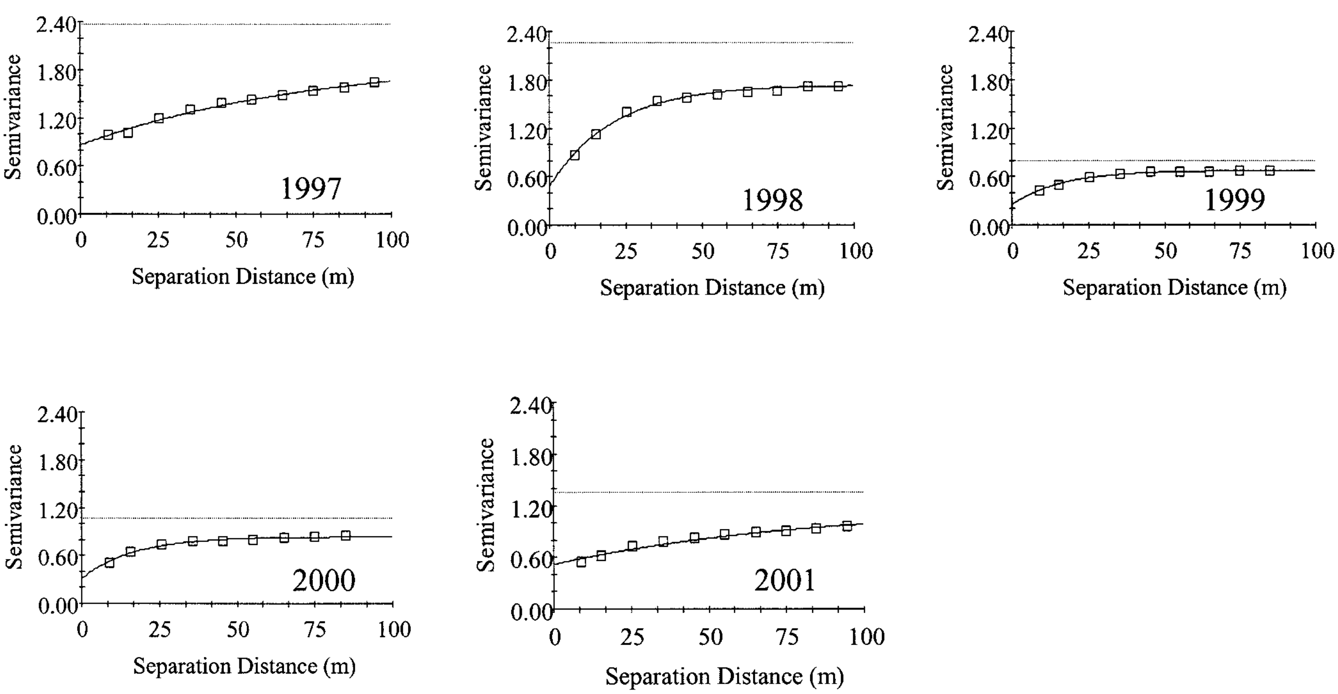

Fig. 5. Semivariance analysis of yield spatial structure, showing variograms for the 1997 through 2001 years at the Gibbon, NE, corn study site.

Table 6. Results of semivariance analysis of grain yield spatial variability, showing variogram model (i.e., spherical, exponential, linear) selected and model parameters determined [nugget, sill, and range, coefficient of determination (R^2), and reduced sum of squares (RSS)], for the five growing seasons at the Gibbon, NE, corn study site.

		Variogram model parameters				
Year	Model	Nugget	Sill	Range	R^2	RSS
1997	Exponential	0.861	1.994	75	0.995	0.0065
1998	Exponential	0.482	1.733	21	0.992	0.0078
1999	Exponential	0.253	0.674	16	0.993	0.0005
2000	Exponential	0.311	0.834	16	0.980	0.0019
2001	Exponential	0.517	1.198	85	0.986	0.0078

similar to MZ than in the other 2 yr. Whereas in 1999 and 2000, regions of similar yield were smaller, more randomly located, and less similar to MZ patterns than in the other 3 yr.

We also compared average yields among the four MZ (Fig. 6), adjusting for the unique spatial structure of yield variability for each year (Table 6) in the analysis of variance, as a way of comparing MZ effects on yields. We observed that average yields among the four MZ differed markedly in 1997, 1998, and 2001 (Fig. 6), with MZ 1 and 4 producing the highest and lowest yields, respectively, and the other two zones producing intermediate yields. Yields for these three years increased by 16% from MZ 4 to MZ 1, with a maximum increase of 25% in 1997. However, in 1999 and 2000, the wettest and driest seasons, respectively (Table 2), we observed less-pronounced (≤5%) differences in average yields among MZ although differences were statistically significant (Fig. 6). In summary, we observed that while MZ can be used to characterize spatial variation in soil chemical properties, this approach is less consistent in characterizing spatial variability in crop yields since average yields and yield patterns varied considerably from temporal. These results confirm the observations of Eghball and Varvel (1997), Lamb et al. (1997), and Machado et al. (2002) regarding the role climate variability plays in altering the expression of spatial yield patterns.

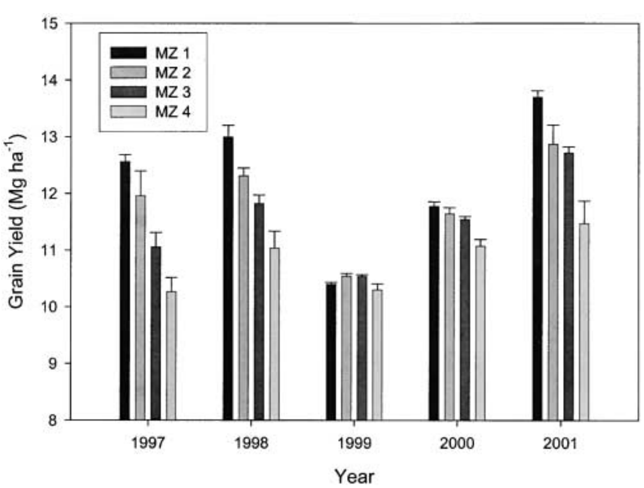

Fig. 6. Average grain yields of the four management zones (MZ), adjusted by yield spatial structure, for five crop seasons at Gibbon, NE, site. Standard error bars, adjusted by yield spatial structure, are shown to compare among yields of MZ within a given year.

The observed changes in spatial yield patterns from year to year were likely due to the interaction of soil factors influencing crop yield with climate variability (Machado et al., 2000, 2002). According to Moore et al. (1993) and Gessler et al. (2000), soil factors that influence crop yield include landscape factors controlling water distribution (i.e., elevation and slope), physical properties affecting water-holding capacity (i.e., texture and bulk density), and chemical properties affecting fertility (i.e., pH, EC, and OM). For example, we observed that spatial variation in yields was more strongly influenced by MZ in the years of average precipitation (Table 2) of 1997, 1998, and 2001 compared with wetter or drier years of 1999 and 2000, respectively. Thus, changes in spatial patterns for yield across years were likely due to changes in spatial variability of available soil water across the various growing seasons. For example, during seasons of average precipitation, field areas of lower elevation, flatter slope, and deeper profile associated with MZ 1 likely possessed more optimal soil water conditions throughout the season and, hence, higher crop productivity than the area of MZ 4 with higher elevation, greater soil erosion, and shallower depth (Moore et al., 1993; Gessler et al., 2000). This would be true even under the irrigated condition of this study since the sprinkler irrigation system used was only capable of uniform applications of water even though soil properties affecting water-supplying capacity varied considerably across this field. Combined with the more optimal soil fertility properties observed for MZ 1 vs. MZ 4 (Table 4), it is not surprising that higher crop yields were found in MZ 1 vs. MZ 4 (Fig. 5). Kravchenko and Bullock (2000) and Kaspar et al. (2003) also observed negative associations between corn yield and elevation. However, during the rainy season of 1999, soil moisture conditions were observed to be extremely wet, resulting in occasional ponding in the lowland regions of MZ 1. This was especially apparent during June when recorded precipitation and solar radiation amounts (data not shown) were 78% above and 13% below the long-term average, respectively, for this location. The soil survey (USDA Soil Conserv. Serv., 1974) describes the soils of MZ 1 (Fig. 1) as being prone to flooding in rainy seasons. The more saturated soils of MZ 1 would in turn have likely experienced higher N losses through denitrification and/or leaching than the upland soils of the other MZ (Dinnes et al., 2002), resulting in increased crop N stresses. That significant crop stresses occurred in 1999 is confirmed by the relatively low yields observed for the 1999 field vs. yields of the other four seasons (Table 2 and Fig. 6), and these stressful conditions, apparently, resulted in less-pronounced differences in yields among MZ in this year (Fig. 6). The lack of pronounced yield differences among MZ in the drier season of 2000 is, however, more difficult to explain. Perhaps, it was caused by abiotic or biotic factors that we did not measure. Regardless of the cause, the observed changes in average yields and spatial patterns in 1999 and 2000 compared with the other 3 yr illustrates the significant role temporal variability plays in the expression of spatial yield patterns, even under irrigated conditions.

SUMMARY AND CONCLUSIONS

Variability in several measured landscape attributes, including soil brightness, elevation, and EC_a, was aggregated into MZ to determine if these attributes could be used to characterize spatial variation in soil chemical properties as well as grain yield patterns and if temporal variability affects expression of spatial patterns in yields. It appears that landscape attributes can be used to delineate MZ that characterize spatial variation in soil chemical properties; however, this approach is less consistent in characterizing spatial variability in yields across temporal variations in climate. The relative importance of various soil properties in predicting yield depends on the most limiting factor. In many situations, that factor is water. Perhaps farmers could use landscape attributes and yield data from multiple years to identify and describe recurring spatial yield patterns in their fields and hence provide opportunities for site-specific management of crop inputs like N. Though for farming by MZ to be effective, it is necessary to demonstrate a strong and consistent relationship between the soil-derived properties used to delineate MZ and spatial patterns in yields over yearly variations in climate. However, we observed significant temporal changes in yield spatial patterns, even under the irrigated conditions of this study. Use of MZ for variable application of inputs like N would only have been appropriate for this field in three out of the five seasons, seriously restricting the use of this approach under variable environmental conditions. It seems unlikely that the static soil-based MZ concept alone will be adequate for variable application of crop inputs like N across temporal variability. Alternatively, a better strategy might be to combine the use of MZ along with crop-based in-season remote sensing systems (Raun et al., 2002; Shanahan et al., 2003), where crop N status can be instantaneously assessed under ever-changing climatic condition, to more efficiently apply crop inputs such as N.

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