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Feasibility of Site-Specific Management of Corn Hybrids and Plant Densities in the Great Plains[1]

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Abstract. The goal of this research was to determine the potential for use of site-specific management of corn hybrids and plant densities in dryland landscapes of the Great Plains by determining (1) within-field yield variation, (2) yield response of different hybrids and plant densities to variability, and (3) landscape attributes associated with yield variation. This work was conducted on three adjacent fields in eastern Colorado during the 1997, -98, and -99 seasons. Treatments consisted of a combination of two hybrids (early and late maturity) and four plant densities (24,692, 37,037, 49,382 and 61,727 plants ha^{-1}) seeded in replicated long strips. At maturity, yield was measured with a yield-mapping combine. Nine landscape attributes including elevation, slope, soil brightness (SB) (red, green, and blue bands of image), EC$_a$ (shallow and deep readings), pH, and soil organic matter (SOM) were also assessed. An analysis of treatment yields and landscape data, to assess for spatial dependency, along with semi variance analysis, and block kriging were used to produce kriged layers (10 m grids). Linear correlation and multiple linear regression analysis were used to determine associations between kriged average yields and landscape attributes. Yield monitor data revealed considerable variability in the three fields, with average yields ranging from 5.43 to 6.39 mg ha^{-1} and CVs ranging from 20% to 29%. Hybrids responded similarly to field variation while plant densities responded differentially. Economically optimum plant densities changed by around 5000 plants ha^{-1} between high and low-yielding field areas, producing a potential savings in seed costs of $6.25 ha^{-1}. Variability in yield across the three landscapes was highly associated with landscape attributes, especially elevation and SB, with various combinations of landscape attributes accounting for 47%, 95%, and 76% of the spatial variability in grain yields for the 1997, -98, and -99 sites, respectively. Our results suggest site-specific management of plant densities may be feasible.

Keywords: maize, spatial variability, geostatistics, variable rate planting

Abbreviations: GIS, geographical information systems; DGPS, differential global positioning system; EC$_a$, apparent electrical conductivity; SOM, soil organic matter.

[1]Mention of commercial products and organizations in this article is solely to provide specific information. It does not constitute endorsement by USDA-ARS over other products and organizations not mentioned.

Introduction

Modern farmers are keenly aware of the productivity differences in their fields, and recognize the potential value of using variable rate technology versus uniform application rates in managing crop production inputs. Images depicting highly variable crop growth within fields are often used to advance the intuitive appeal of variable rate farming. However, only manageable and predictable sources of within-field variation can be exploited to cover the cost of variable rate application.

Seeding different crop varieties on the go at variable plant densities is techno-logically feasible. Precision farming pioneers have predicted that crop variety will be the second most important input for variable rate management (Dudding *et al.*, 1995). Crop variety is an ideal subject input for precision farming because yield variation due to variety selection is ultimately manageable, i.e., plant the optimum variety in different parts of the field. Numerous researchers (Giauffret *et al.*, 2000; Kang and Gorman, 1989; Signor *et al.*, 2001) have demonstrated the presence of significant genotype-by-environment interaction, suggesting the potential for vari-able genotype application.

While Bullock *et al.* (1998) observed differences in economically optimal plant densities as a function of yield potential in an extensive study in the Corn Belt region of the US, they concluded that variable rate seeding would be infeasible, because of the high cost associated with characterizing site variability. However, in the western Great Plains region of the US, where annual precipitation averages only 350–432 mm, drought stress is a more limiting factor than in the midwestern Corn Belt region. Research for the Great Plains region (Gardner and Gardner, 1983; Larson and Clegg, 1999; Norwood, 2001) indicates that optimal plant densities and hybrid selection (short- versus long-growing season) for dryland production are highly dependent on available seasonal water, with lower plant densities and shorter season hybrids recommended for conditions with reduced available seasonal water. Thus, we hypothesized that the optimal combination of hybrid maturity (short versus long) and plant densities (low versus high) would change according to variation in yield potential across the landscape, and variation in yield potential may be related to change in topographic and soil quality features which affect available soil water and crop growth.

Moore *et al.* (1993) proposed a GIS terrain analysis method, involving use of a digital elevation data in conjunction with soil maps, as a means of predicting landscape variation in several soil attributes associated with crop productivity, including available soil water. Recent research in precision agriculture has focused on the use of management zones as a method to categorize landscape variation. Management zones, in the context of precision agriculture, refer to geographic areas that possess homogenous attributes in terrain 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 management zones vary. Topography has been suggested as a logical basis to define homogenous zones in agricultural fields (Franzen *et al.*, 1998), and was found to be a useful method by Kravchenko and Bullock (2000). Aerial photographs, bare soil or

crop canopy images, and yield maps have also been suggested as approaches to delineate management zones (Schepers *et al.*, 2000). Remote sensing technology is especially appealing to identify management zones, 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 management zones is increasing (Varvel *et al.*, 1999). Another promising noninvasive approach to define the boundaries of management zones involves the use of magnetic 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 percent clay (Sudduth *et al.*, 1998).

   The goal of this research was to estimate potential for use of site-specific management of corn hybrids and plant densities for dryland landscapes in the Great Plains by determining (1) within-field yield variation, (2) yield response of different hybrids and plant densities to variability, and (3) landscape attributes associated with yield variation.

Materials and methods

Experimental treatments and field design

This work was conducted in three adjacent fields located near Anton, CO (approximate coordinates are 39.62949 °N, −103.05 °W) during the 1997, 1998, and 1999 growing seasons (Figure (1). Soils of the fields are classified as Argiudolls with silt loam and silty clay loam surface textures. The area for each study was
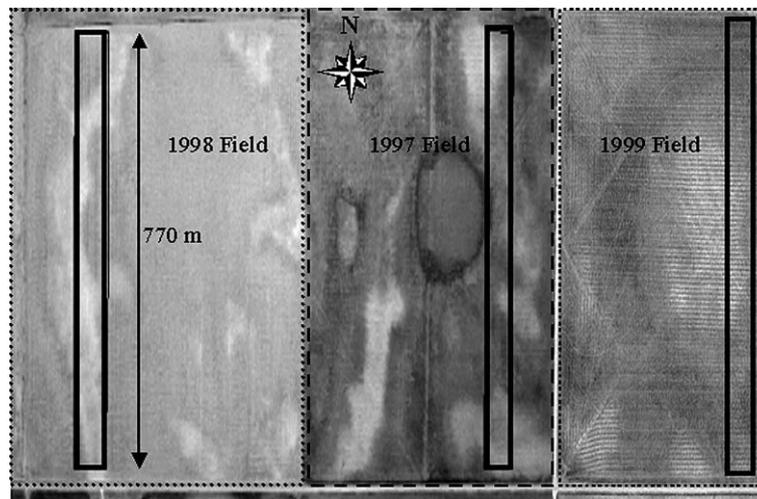
Figure 1. Aerial photograph taken in early spring (March 20) 1999, depicting three adjacent field sites for dryland corn study. The soil surface was covered with dormant wheat for the 1997 site, corn residue for the 1998 site, and wheat residue for the 1999 site. Location of study sites within each field is depicted with rectangles.

approximately 6 ha. No-till cropping practices were utilized in a winter wheat (*Triticum aestivum*)—corn (*Zea mays*)—fallow crop rotation. Weed control during fallow and cropping periods was accomplished with the combined application of contact- (glyphosate) and soil-applied residual herbicides (triazine) at labeled rates, with the goal of maintaining weed free conditions to maximize available soil water for crop use. Nitrogen fertilizer was broadcast applied as liquid solution (32% N) just prior to planting based on field soil test values and a yield goal of approximately 7500 kg ha^{-1} for the entire field. Liquid fertilizer (10-34-0) was applied at the rate of 94 L ha^{-1} in the furrow at planting, providing approximately 18 kg ha^{-1} of P. Temperature data were obtained for all three growing seasons from the High Plains Climate Center Network (University of Nebraska) through the use of an automated weather station at the USDA Central Great Plains Research Station at Akron, CO that is located about 40 km north of the research sites. Precipitation was recorded for each season on site.

Treatments consisted of a factorial combination of two adapted hybrids (Pioneer® Brand 3752, late maturing and 3860, early maturing) and four seeding rates (only three in 1997) designed to obtain final plant densities of approximately 24,692, 37,037, 49,382 and 61,727 plants ha^{-1}. The experimental design was a randomized block design in a split plot treatment arrangement with density levels as main plots and hybrids as subplots, and replicated three (1997) or four times (1998 and 1999). Individual treatments were seeded in long, narrow strips (3.1 by 770 m), consisting of four rows (0.762 m row spacing). An eight-row planter was used, with seed of each hybrid placed in four units of the planter, while seeding a specific density level.

Harvest procedures

Harvest plant densities were evaluated for all treatment combinations by actual field measurements at approximately 15 locations in each treatment strip, using a 2 m section of row. At maturity, crop yield and grain moisture were determined by harvesting all four rows of each treatment strip with a continuous-flow Micro-Trak® (Micro-Trak Systems; Eagle Lake, MN) yield monitor mounted on a John Deere (model 6600) combine and interfaced to a DGPS system (Trimble model 124, Sunnyvale, CA) to provide yield data for all treatment combinations, logging readings each second. The plots were harvested in the same direction of travel to minimize errors associated with combine grain flow dynamics. The yield monitor was calibrated to weigh wagon measurements. Yield data were processed and mapped with Farm HMS® software (Red Hen Systems, Fort Collins, CO). Grain yields were adjusted to a constant moisture basis of 155 g kg^{-1} water.

Acquisition of landscape attributes

Elevation measurements for all fields were obtained from the DGPS receiver associated with the combine yield monitor. The combine traversed the entire field while harvesting all treatment strips (3.1 m wide), and hence, high-density elevation data

were acquired for each site. An aerial photograph of the soil surface, with crop residue present, was acquired on the same date (March 20, 1999) for all three sites, with a 35 mm camera mounted in an aircraft using Kodak Ektachrome color film. The aircraft was flown at an altitude of approximately 2130 m during image acquisition. Four targets (white-painted 1.2 × 2.4 m wood sheets) were placed at the corners of each research plot area to assist with georegistering the image. Geological coordinates were obtained for the targets with DGPS receiver for use in the image georegistration process. The 35 mm color slide was scanned, input into Imagine® GIS software (ERDAS; Atlanta, GA), and geo-referenced, with a nominal ground resolution for the image of 1 m. Soil surface brightness was expressed as reflectance intensity [digital number (dn)] in the red, green, and blue spectral bands in the digitized image.

The EC_a attribute was mapped prior to planting in each year using a Model 3100 Veris® conductivity sensor (Veris Technologies, Salina, KS). The sensor measures conductivity by direct soil contact with four probes, providing shallow (0–30 cm) and deep (30–120 cm) measurements of EC_a. The sensor was pulled (6 km h^{-1}) through the field with a truck on parallel swaths at 20 m intervals. EC_a data were geo-referenced using a DGPS receiver mounted on the top of the truck cab. Data were collected at one-second intervals and stored in a data logger.

Prior to planting, each site was grid sampled (0.203 ha grids) using a systematic unaligned scheme to obtain soil chemical properties. Within a 10 m radius of each sampling point, ten soil cores were collected to a 15 cm depth and composited. Samples were analyzed for pH and soil organic matter (estimated from soil organic carbon). Total carbon was determined using the Dumas dry combustion technique (Schepers *et al.*, 1989).

Statistical analysis

To assess the degree of spatial dependency and determine the spatial structure of grain yields for each treatment combination (hybrid × plant density) in each year, we inputted the yield monitor data for the replicated strips of each treatment as separate data layers into the geostatistical package GS +® (Gamma Design Software, Plainwell, MI). Likewise, data for all landscape attributes [elevation, apparent shallow and deep EC_a, pH and soil organic matter (SOM)], except soil brightness (SB) (digital for image red, green, and blue band), were analyzed for spatial structure. First, the extent of spatial dependency or autocorrelation 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, semi variance analysis was conducted to determine the spatial structure for each variable. Semi variance is an autocorrelation statistic defined as $\gamma(h) = [1/2N(h)] \: \Sigma[z_i - z_i + h]^2$, where $\gamma(h)$ = semi variance 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. Various semivariogram models were evaluated (i.e., spherical, exponential, linear, and gaussian) to determine which best fit the spatial structure of each variable. The program uses reduced sums of squares (RSS) values to choose models and model parameters that minimize RSS. Semivariogram 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 semivariogram models to produce interpolated maps with 10 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 its' value estimated via kriging as though it were never present. In this way a comparison can be made of estimated versus actual values for each sample location in the domain, and coefficients of determination used to assess goodness of fit. For the SB data, inverse distance weighting was used as an alternative to kriging to produce interpolated surfaces, because of the high spatial resolution (1 m) of this data.

To compare and evaluate the yield responses of individual treatments (hybrid by plant density) to field variation, kriged values for all treatment combinations, treatment averages, and landscape attributes were exported from GS + package into the GIS package MapCalc® (Red Hen Systems, Fort Collins, CO), maintaining separate layers for each treatment and landscape attribute with the same 10 m grid structure (see Figures 3 and 4). An additional landscape attribute slope, which provides an indication of water distribution over the landscape (Kravchenko and Bullock, 2000), was created in MapCalc by applying the slope function to the elevation layer. This function creates a map indicating the slope (1st derivative) along a continuous surface. Slope values for each cell are calculated using the eight neighbor cells, that is, a 3×3 window is used for each calculation. The value is applied as a percent, to the centroid of the center cell. The default procedure aligns a best-fitted plane to the values in the window, and assigns the slope of the plane to the center cell. The window then shifts over one cell and the process repeats.

To further evaluate the response of treatment grain yields to field variation, grid values for each data layer (treatment grain yields and landscape attributes) were exported from MapCalc® to spreadsheet format. The data were then sorted based on average treatment yields into low-, medium-, and high-yielding field areas using the mean and standard deviation for each field. Low-yielding areas comprised regions one standard deviation below the field average and high-yielding areas were one unit above the mean, with medium-yielding areas comprised of the remainder of the field. Then plant density response curves were developed by fitting quadratic curves to grain yield data as a function of plant density. Plant density response functions (production functions) were fit, using Sigma Plot® (SPSS Science; Chicago, IL), to the yield data by hybrid and field yield level, for each site (for 1998 curves shown in Figure 5). The marginal physical product or first derivative of the yield response

functions was then computed. The marginal physical product plant density curves were then graphed by price ratios (price of seed/price of grain) to generate the demand curves (Figure 7). The demand curves show the optimum plant density for alternative seed-grain price ratios.

To determine the relative importance of the nine landscape attributes in explaining spatial variation in grain yield we utilized linear correlation and multiple linear regressions analysis with SAS PROC REG (SAS Inst., Cary, NC) with landscape attributes as independent variables and average grain yields as the dependent variable. Forward stepwise regression procedure was used, and only parameters significant at $P \leq 0.15$ were retained in the final regression models.

Results and discussion

Assessment of field variability

The combine yield monitor revealed a considerable amount of within-field variability for each of the three sites, with average yields ranging from 5.43 to 6.39 mg ha^{-1} (highest for 1999 site) and CVs ranging from 20% to 29% (Table 1). The higher grain yields for 1999 versus 1997–98 were likely due to above average precipitation (30% above long-term average) received during this growing season (Figure 2), particularly during the critical month of August when reproductive and grain filling

Table 1. Statistical parameters for grain yield and landscape attributes of elevation, soil brightness (SB) (digital number (DN) for red, green and blue bands of aerial image), apparent electrical conductivity (EC$_a$) for shallow (0–0.3 m) and deep (0–1 m) soil layers, pH, and soil organic matter (SOM) of three dryland corn study sites

| | Grain | | | SB | | EC$_a$ | | | |
Statistics	Yield (mg ha^{-1})	Elevation (m)	Red (DN)	Green	Blue	Shallow (ms m^{-1})	Deep	pH	SOM (g kg^{-1})
1997									
n	4112	4112	32181	32181	32181	3125	3125	27	27
Mean	5.43	1429	146	142	140	50.4	49.3	7.87	15
SD	1.16	1.9	12	11	10	11.5	10	0.05	0.4
CV(%)	21.3	0.1	8.2	7.8	7.2	22.8	20.3	0.6	2.6
1998									
n	5002	5002	40927	40927	40927	2950	2950	33	33
Mean	5.88	1439	190	188	207	26.9	27.9	7.98	18
SD	1.71	2.7	12	12	12	4.9	4	0.03	0.4
CV (%)	29.1	0.2	6.3	6.4	5.8	18.2	14.3	0.4	2.2
1999									
n	4552	4552	38376	38376	38376	2847	2847	32	32
Mean	6.39	1425	157	147	164	32.9	36.3	7.24	17
SD	1.28	3.1	14	14	13	5.3	5.4	0.05	0.4
CV (%)	20.0	0.2	8.9	9.5	7.9	16.1	14.9	0.7	2.4
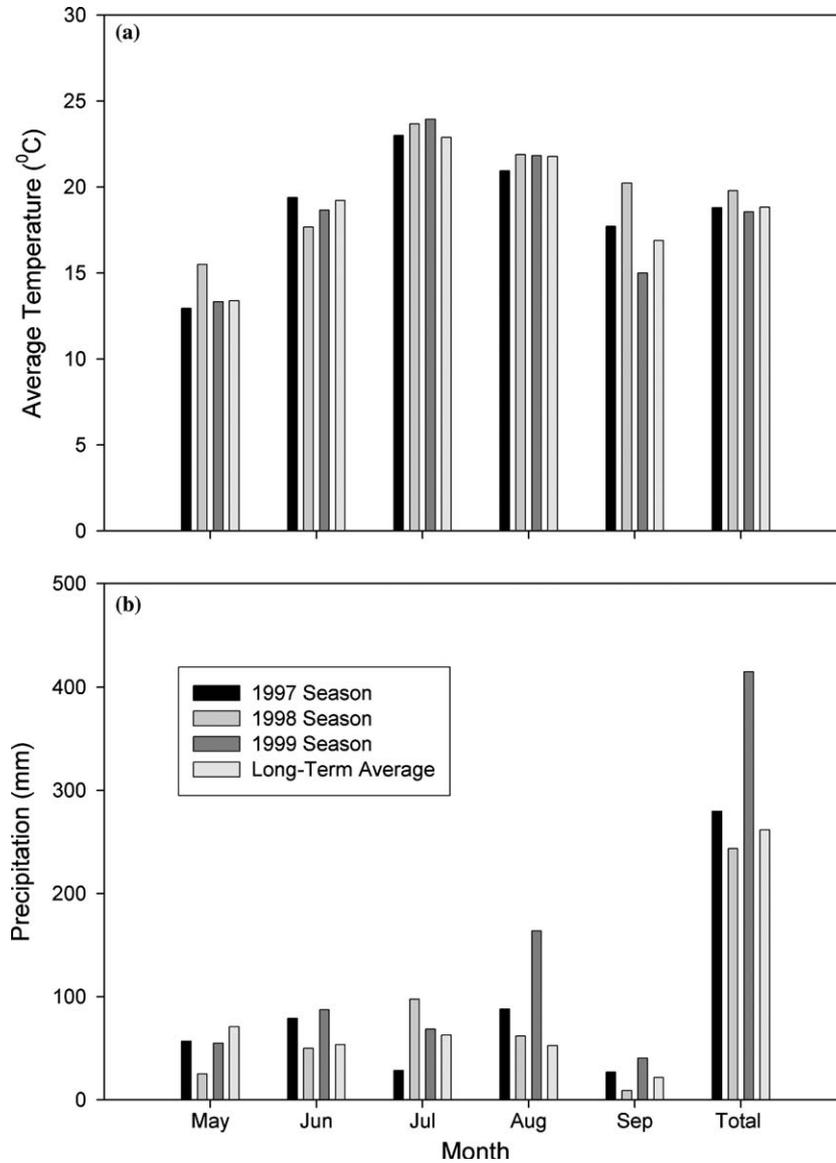
Figure 2. Climatological data (average monthly temperature and precipitation) for the 1997, 1998, and 1999 corn growing seasons as well as 50-year long-term averages.

processes occurred. Elevation also varied significantly for the three sites, with differences of around 5, 11, and 14 m for the 1997, 1998 and 1999 sites, respectively. Even though the soil surface at all three sites was covered with crop residue (growing wheat for 1997, corn in 1998, and wheat in 1999), the aerial photograph taken in early spring of 1999 (Figure 1) revealed a considerable amount of variation in SB, expressed as DN for the red, green, and blue spectral bands, with CVs for the bands

ranging between 6% and 10% (Table 1) across the three sites. Likewise, variation was observed for other measured landscape attributes including EC_a (shallow and deep), pH, and SOM. Thus, measurement of both crop yields and landscape attributes indicated there was substantial field variability at the three study sites for evaluating yield responses of hybrid and plant density treatments.

Assessment of spatial structure of data

The variation in grain yields for all treatment combinations, as well as variation in landscape attributes, was spatially dependent at all three sites as determined by Moran's *I* test (data not shown), providing justification for semi variance analysis to identify appropriate semi-variogram models and parameters for all data layers. Utilizing appropriate semivariogram models and block kriging, kriged surfaces for treatment grain yields and landscape attributes were generated. Examples of maps generated from the kriging process, depicting spatial patterns for 1998 treatments yields and selected landscape attributes for all three sites are shown in Figures 2 and 3, respectively. The coefficient of determination (r^2) values for cross-validation analysis of kriged grain yield surfaces of eight treatment combinations, ranged from a low of 0.290 to a high of 0.648 across sites. For the nine landscape attributes, coefficients ranged from a low of 0.352 to a high of 0.933 across sites. Thus, the procedures we utilized to generate kriged surfaces for grain yields and landscape attributes produced distinct and consistent spatial patterns, which agreed reasonably well with the original raw data collected for each layer. For example, at the 1998 site, increasing plant densities resulted in higher yield values for both hybrids (Figure 3a–h,), particularly for the northern portion of the field. The yield map representing average yields across treatments (Figure 3i) revealed the most productive or high-yielding area of the 1998 field was located to the north, while medium- and low-yielding areas were positioned more southerly. The spatial patterns of average grain yields (regarding north–south gradient) in 1998 appear to be similar to spatial patterns of selected landscape attributes such as elevation (Figure 4b). For example, the lower-yielding area of the southern portion of the field appears to have lower elevation. Likewise, spatial patterns in average grain yields at the other two sites appeared to be associated with spatial patterns of landscape attributes (Figure 4a and c).

Response of treatments to field variation

Plant density production functions were developed for each treatment combination by fitting quadratic equations to grain yield responses as a function of plant density, hybrid, and yield level (low-, medium, and high-yielding field areas). The final average established plant density values determined by stand counts was 28,321, 43,560, 59,514 plants ha^{-1} in 1997, 25,679, 39,259, 53,827, 66,420 plants ha^{-1} in 1998, and 27,822, 40,442, 50,765, 63,388 plants ha^{-1} in 1999, with no stand differences observed between hybrids (data not shown). Results for 1998 (Figure 5) indicate that a quadratic function provided a good fit to all treatment combinations,
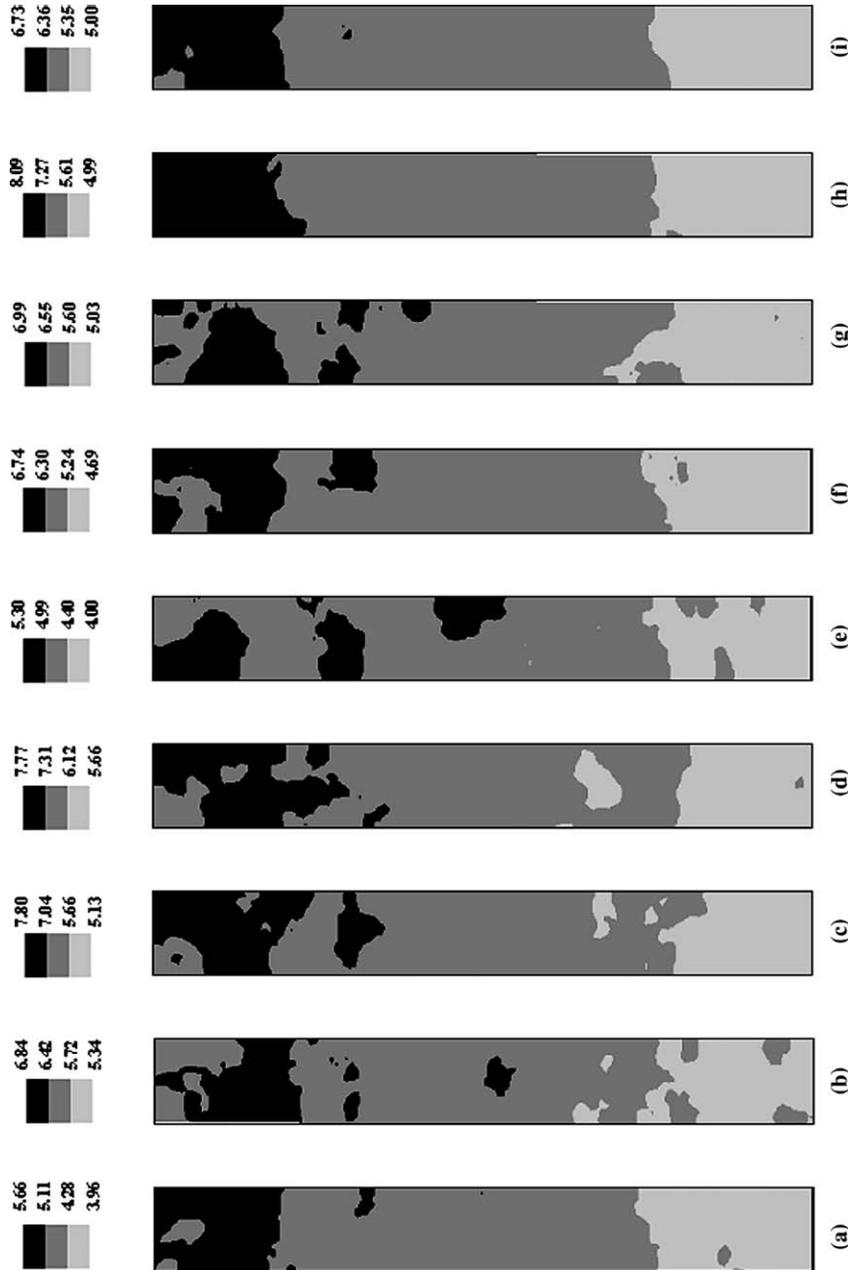
Figure 3. Grain yield (mg ha^{-1}) maps and legends depicting the response of Pioneer 3752 (a–d) and Pioneer 3860 (e–h) to four plant density treatments (25,679, 39,259, 53,827 and 66,420 plants ha^{-1}), and average yield across all treatments (i) in 1998. The treatment average yields portrayed in (i) are categorized into low- (light) and high-yielding (dark) areas, with low- and high-yielding areas one standard deviation below or above the field average, respectively. The gray shaded area is represented by medium-yielding region of the field.
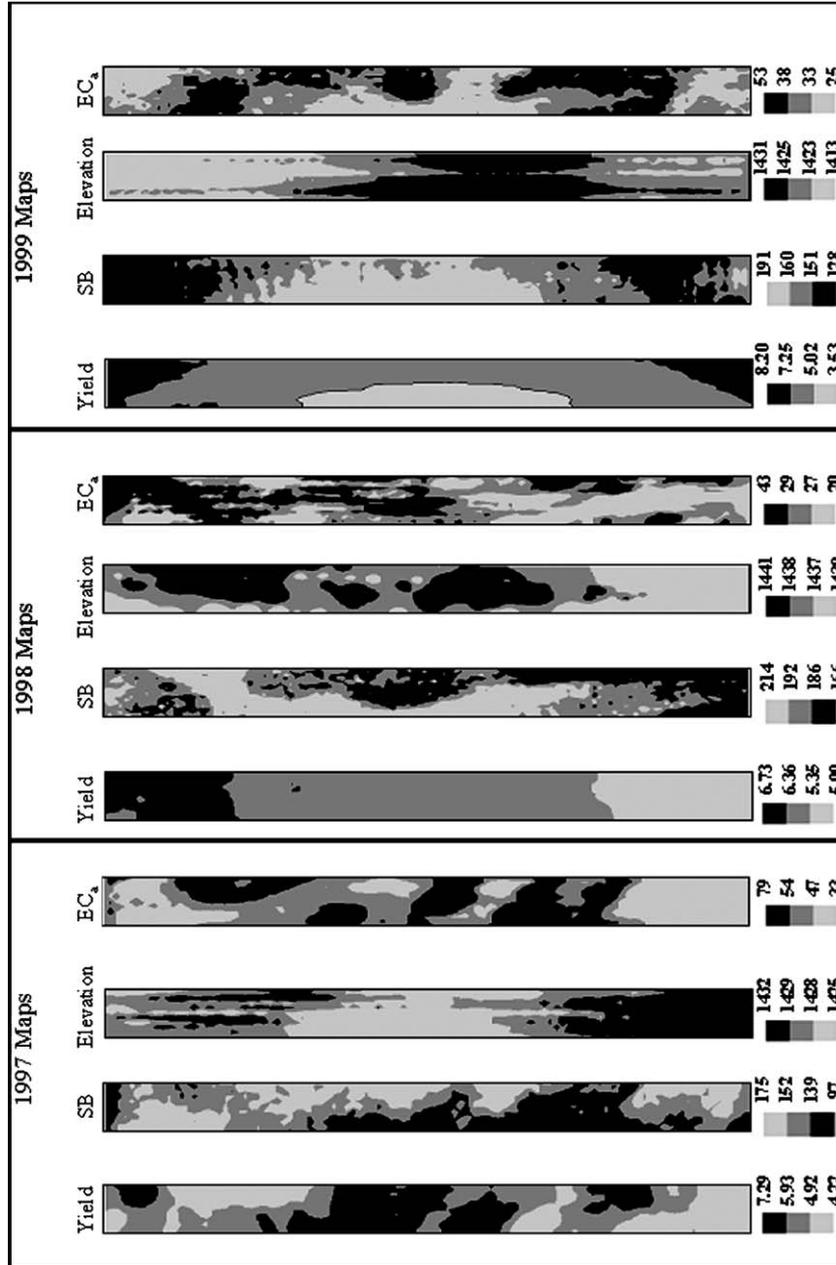
Figure 4. Maps and legends depicting average grain yield (mg ha^{-1}) and selected landscape attributes of soil brightness (SB) or digital number for red band, elevation (m), and apparent electrical conductivity (EC$_a$ in ms m^{-1}) for the 1997, 1998, and 1999 dryland corn study sites.

Figure 5. Grain yield response of two hybrids (Pioneer 3752 and 3860) to four plant densities in the (a) low-, (b) medium-, and (c) high-yielding areas of the 1998 field.

based on the large coefficients of determination for each curve. It also appeared that the two hybrids responded similarly to increasing plant density levels, with hybrid 3752 maintaining a slight advantage over hybrid 3860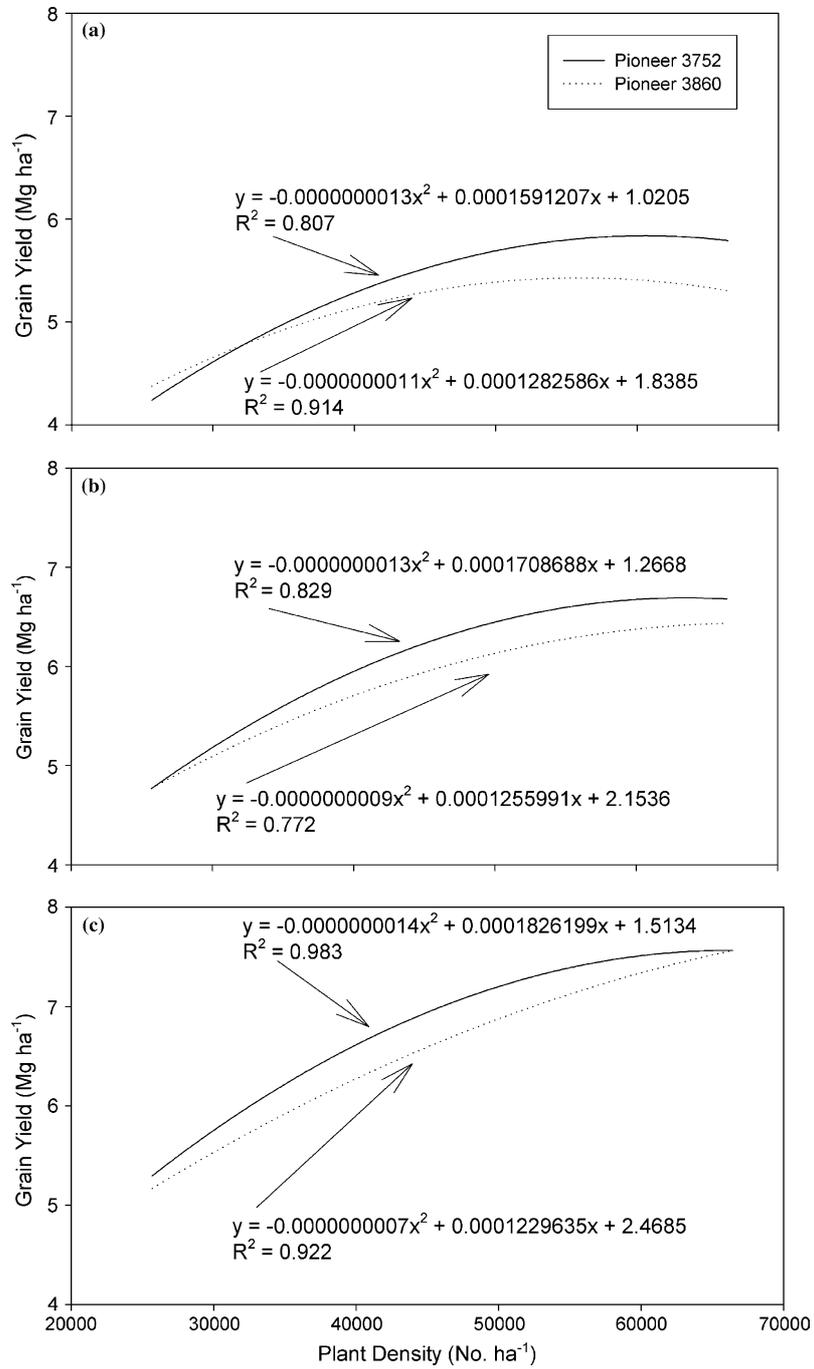 across most of the plant densities and yield levels, with similar trends observed in 1997 and 1999 as well (data not shown). Since there was no interaction of hybrid by plant density or yield level, we conclude there is little justification for site-specific management of the hybrids used in this study. These results are contrary to our initial hypothesis that shorter season hybrids would have an advantage over longer-seasons hybrids in lower yielding, more drought prone regions of the field, while longer season hybrids would flourish in high-yielding areas of the field. Additionally, our results contrast with the recommendations of Norwood (2001), who suggested that hybrid maturity should be diversified for risk management under drought conditions. However, the subset of hybrids used in our work was more limited than those of Norwood (2001). It is conceivable that use of more diverse hybrids or more extreme environmental conditions (average to above precipitation, Figure 2) in our work could have produced different results.

To evaluate the plant density response functions across the three study sites we pooled data for the three sites and averaged across hybrids, separating data from each field into low-, medium- and high-yielding field areas (Figure 6). Again, it appears that a quadratic function provided a reasonable fit to the pooled data, based on the large coefficients of determination. This figure illustrates that grain yield increased around 50% in response to increasing plant density for high-yielding areas, while it increased only 25% in low-yielding areas, with the medium-yielding area

The equations shown in the figure:

$$y = -0.0000000018x^2 + 0.0002352199x + 0.1164$$
$$R^2 = 0.870$$

$$y = -0.0000000013x^2 + 0.0001521115x + 1.7200$$
$$R^2 = 0.763$$

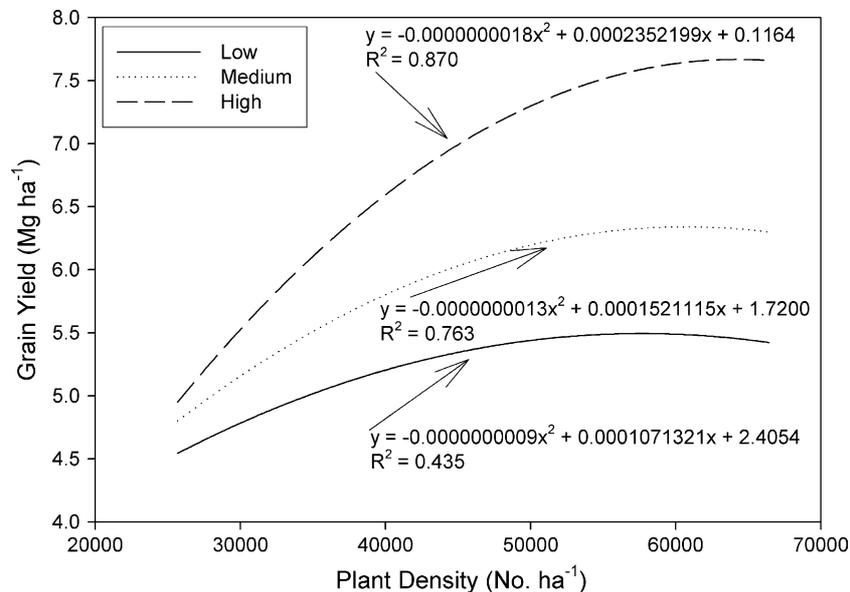$$y = -0.0000000009x^2 + 0.0001071321x + 2.4054$$
$$R^2 = 0.435$$

Figure 6. Average (over two hybrids) grain yields response to four plant densities in the low-, medium, and high-yielding areas of the 1997, 1998 and 1999 fields.

providing an intermediate response. Interestingly, while response to increasing plant density was less dramatic for low- versus high-yielding areas, we did not observe a decline in grain yields over the range of densities we evaluated, which is contrary to the findings of Norwood (2001) under low-yielding drought-stressed conditions. The differences in our results versus those of Norwood (2001) were again likely due to the more extreme drought conditions in the latter work, as precipitation received (Figure 2) during our study was average or above. Another factor likely contributing to this response is the fact that modern corn hybrids have become increasingly tolerant of higher plant densities, even under adverse environmental conditions (Nafziger, 1994). Nonetheless, our results suggest different plant density optima for low-, medium, and high-yielding areas of the fields.

Economic analysis of plant density response

To determine the economic optimum for each plant density by yield level curve (Figure 6), derived demand curves (Figure 7) were computed. Demand curves show the optimum plant density to apply for alternative seed-grain price ratios. For example, using seed cost of $1.25 1000 seed^{-1} and grain price of $98.33 mg^{-1} as per Bullock *et al.* (1998), the economic optimum plant density (Figure 7) would be around 60,000 plants ha^{-1} for the low- and medium-yielding areas and approximately 65,000 plants ha^{-1} for the high-yielding area. With a difference in economic optimum of around 5000 plants ha^{-1}, a savings of $6.25 ha^{-1} in seed costs could be
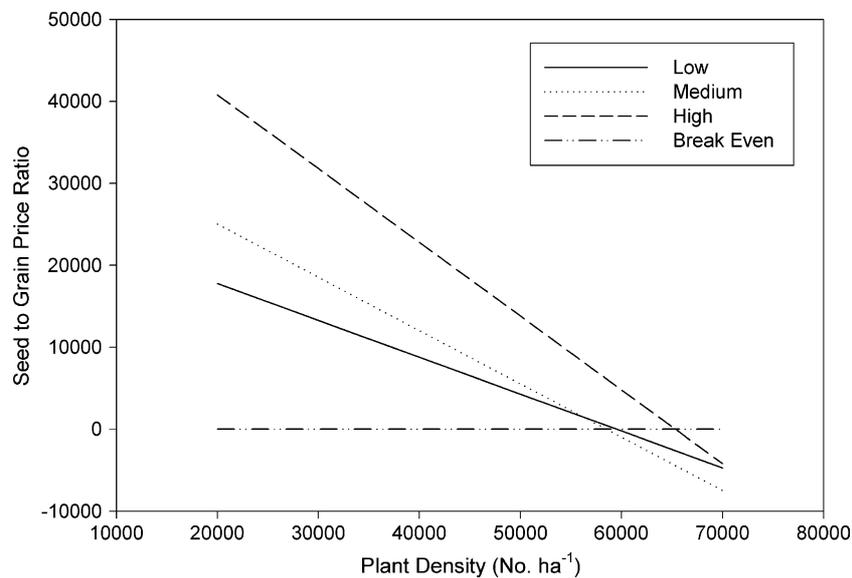

Figure 7. Derived demand curves for low-, medium, and high-yielding areas of the 1997, 1998, and 1999 fields. The break-even price ratio of 0.0128 used for this example is calculated with a seed cost of $1.25 1000 seed^{-1} and grain price of $98.33 mg^{-1}.

realized by reducing plant densities from the high-yielding to the medium- and low-yielding areas; thus, confirming our hypothesis that optimal plant density changes according to variation in yield potential across the landscape. Lowenberg-DeBoer (1998) also suggested that variable seeding rates might be justified in fields with regions yielding less than 5.60 mg ha^{-1}. Hence, there appears to be some justification for site-specific management of plant density in the Great Plains environment, provided a practical means can be developed for characterizing site variability.

Table 2. Linear correlation matrix for grain yield and landscape attributes of elevation, SB (digital number (DN) for red, green and blue bands of aerial image), apparent electrical conductivity (EC$_a$) for shallow (0–0.3 m) and deep (0–1 m) soil layers, pH, and soil organic matter (SOM) for the 1997, 1998, and 1999 corn study sites.

	Yield	Elevation	Slope	Blue	Green	Red	Shallow EC$_a$	Deep EC$_a$	pH	SOM
1997										
Yield	1.000									
Elevation	−0.663	1.000								
Slope	0.009	−0.078	1.000							
Blue	−0.104	0.155	−0.048	1.000						
Green	−0.082	0.080	−0.007	0.922	1.000					
Red	−0.152	0.120	0.032	0.856	0.915	1.000				
Shallow EC$_a$	0.112	−0.392	0.112	−0.472	−0.510	−0.417	1.000			
Deep EC$_a$	0.099	−0.307	0.086	−0.516	−0.610	−0.522	0.858	1.000		
PH	−0.154	0.367	−0.114	0.439	0.473	0.376	−0.681	−0.748	1.000	
SOM	0.463	−0.527	−0.075	−0.103	−0.211	−0.206	0.501	0.451	−0.519	1.000
1998										
Yield	1.000									
Elevation	0.587	1.000								
Slope	0.001	−0.098	1.000							
Blue	0.240	0.534	0.043	1.000						
Green	0.198	0.493	0.060	0.964	1.000					
Red	0.332	0.474	0.085	0.883	0.906	1.000				
Shallow EC$_a$	0.043	0.015	−0.111	−0.376	−0.400	−0.396	1.000			
Deep EC$_a$	0.410	0.217	−0.084	−0.096	−0.118	−0.054	0.559	1.000		
PH	−0.964	−0.491	−0.022	−0.212	−0.170	−0.324	−0.011	−0.406	1.000	
SOM	0.685	0.286	0.004	0.243	0.210	0.330	−0.014	0.223	−0.764	1.000
1999										
Yield	1.000									
Elevation	−0.710	1.000								
Slope	−0.069	−0.044	1.000							
Blue	−0.762	0.553	0.054	1.000						
Green	−0.765	0.585	0.047	0.953	1.000					
Red	−0.778	0.612	0.051	0.927	0.976	1.000				
Shallow EC$_a$	−0.172	−0.093	0.107	−0.017	−0.021	0.020	1.000			
Deep EC$_a$	0.033	−0.157	0.110	−0.192	−0.212	−0.189	0.733	1.000		
PH	−0.621	0.702	0.055	0.566	0.628	0.663	0.076	−0.056	1.000	
SOM	0.762	−0.614	−0.074	−0.670	−0.700	−0.730	−0.404	−0.160	−0.753	1.000

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

Table 3. Results of step-wise regression analysis of landscape attributes and grain yield variation at three dryland corn study sites

Step	Variable entered	Partial r^2	Model r^2	$C(p)$	F value	$Pr > F$
1997						
1	Elevation	0.361	0.361	233.3	638.3	< 0.0001
2	SOM	0.036	0.396	159.7	66.4	< 0.0001
3	Shallow-EC$_a$	0.045	0.442	65.2	91.5	< 0.0001
4	Red band	0.021	0.463	21.6	45.0	< 0.0001
5	pH	0.006	0.469	10.3	13.3	0.0003
6	Slope	0.003	0.472	5.9	6.4	0.0118
1998						
1	pH	0.930	0.930	915.5	28416.6	< 0.0001
2	Elevation	0.016	0.946	207.9	647.6	< 0.0001
3	SOM	0.004	0.950	43.7	163.2	< 0.0001
4	Shallow-EC$_a$	0.001	0.951	10.8	34.7	< 0.0001
5	Deep-EC$_a$	0.000	0.951	6.7	6.2	0.0130
1999						
1	Red band	0.605	0.605	1184.2	2735.0	< 0.0001
2	Elevation	0.083	0.688	565.2	472.3	< 0.0001
3	SOM	0.043	0.730	245.7	283.2	< 0.0001
4	Blue band	0.016	0.746	129.7	110.3	< 0.0001
5	Shallow-EC$_a$	0.010	0.756	55.3	74.4	< 0.0001
6	pH	0.005	0.761	22.8	34.2	< 0.0001
7	Slope	0.001	0.762	14.0	10.7	0.0011
8	Deep-EC$_a$	0.001	0.763	8.2	7.8	0.0053

Landscape attributes associated with yield variation

We hypothesized that spatial variability in yield potential would be related to changes in landscape attributes (elevation and terrain) that affect available soil water and other important yield determining soil properties (Moore *et al.*, 1993) under the water-limiting conditions of our study. Grain yield was correlated with several landscape attributes across the three study sites (Table 2). To assess the relative importance of the various measured landscape attributes in explaining grain yield variation, we utilized stepwise regression analysis, retaining only significant ($P \leq 0.15$) variables in the final prediction models (Table 3). This analysis revealed that various combinations of landscape attributes accounted for 47%, 95%, and 76% of the spatial variation in average grain yields for the 1997, -98, and -99 sites, respectively. Given that yield is likely a function of other factors not assessed in our work (i.e., distributions of other soil properties or pests), the observed coefficients of determination are surprisingly high.

Elevation measurements appeared to be the most important landscape attribute in explaining spatial grain yield variation, loading as the first or second variable in the models for all three study sites. Associations in spatial patterns between grain yield and elevation were, in fact, observed to varying degrees at all three sites (Figure 4), with higher yields found at lower elevations for 1997 and 1999 fields, while higher yields were observed at higher elevations at the 1998 site. The difference in yield

response to elevation change at the 1998 versus the -97 and -99 sites was due to the
negative association between elevation and pH (Table 2), with pH values of near 8.0
observed at the lower elevations of the 1998 field. These higher pH values at the
lower elevations in 1998 had a strong negative impact (negative model coefficient for
pH) on corn grain yield, with pH accounting for around 93% of the spatial vari-
ability in grain yield (Table 3). Conversely, at the other two sites, higher pH soils
were located at the more eroded higher elevation sites. Nonetheless, there was an
association between spatial variation in grain yield and elevation for all three sites.
This was likely due to the indirect associations between variation in elevation and
variation in soil water availability as shown by Moore *et al.* (1993) and Kravchenko
and Bullock (2002). Additionally, we observed negative correlations between ele-
vation and SOM and positive associations between elevation and pH (Table 2), at all
but the 1998 site. Both pH and SOM were in turn important variables in the yield
prediction models at all three sites (Table 3). Ortega (1997) also found similar
associations between elevation and pH or SOM in a study investigating the spatial
variability of soil properties and dryland crop yields over similar landforms in
eastern Colorado. In summary, our results suggest that use of general landscape
attributes like elevation may provide an indirect means of assessing spatial variation
in soil properties that have direct impact on crop productivity, which is consistent
with the findings of Moore *et al.* (1993) and Gessler *et al.* (2000).

Measurements of SB as a landscape attribute also appeared to be an important yield-
determining variable, accounting for up to 60% (red spectral band of image) of the
spatial variability in grain yield at the 1999 site (Table 3). This is best illustrated in
Figure 4c, where similar spatial patterns for grain yield and SB was observed, with
higher yields found in areas with lower brightness values or darker-colored soils.
Similar, though less distinct, patterns were seen for the 1997 site, while variation in SB
was not associated with yield variation in 1998 (Table 3 and Figure 4). The differences
in association between spatial patterns for SB and grain yield across sites was likely due
to differences in crop residues present during image acquisition, with standing wheat
residue (1999 site) providing the most desirable and corn residue (1998 site) the least
desirable surface for assessing yield-related variation in SB. Mean brightness values of
the spectral bands of the 1998 image were greater than the same spectral bands of the
other two images (Table 1), indicating that corn residue was more reflective than the
other two surfaces. Additionally, soil moisture may have been drier for 1998 versus
1997 and 1999 fields at image acquisition (March 20, 1999), as the 1998 site received the
least amount of precipitation (Figure 2) and was the most recently cropped of the three
fields prior to image acquisition, which would have further increased reflectivity (Lo-
bell and Asner, 2002). Increased reflectivity apparently prevented an accurate assess-
ment of variability in SB for the 1998 site, since SB was not a significant variable in the
yield prediction equation for 1998, but was in 1997 and 1999 (Table 3). Mulla and
Schepers, (1997) have recommended the use of bare soil images for assessing spatial
variation in soil properties. However, in no-till production systems bare soil situations
are not always available. Given these limitations, our results suggest standing wheat
residue would be preferable to either dormant wheat or corn residue for assessing
variation in SB. SB and SOM were negatively associated at the 1997 and 1999 sites,
while they were not related at the 1998 site (Table 2), implying that brighter more

reflective soil areas possessed lower SOM levels. SOM was in turn found to be an important yield determinant at all three locations (Table 3). Hence, our work suggests that assessment of SB using aerial photography has potential for delineating variation in important landscape properties such as SOM, which agrees with the findings of Varvel *et al.* (1999) and Chen *et al.* (2002).

While not as important as elevation or SB, EC_a assessments appear to hold some promise for characterizing field variation, as either the shallow or deep readings were important yield determinants in all three years (Table 3). The correlations (Table 2), both positive and negative, observed between EC_a and other soil properties such as pH and SOM (Table 3) imply that EC_a measurements may provide an indirect assessment of these important soil properties. Our results are consistent with the findings of Johnson *et al.* (2001) who found that EC_a measurements would be a useful tool for delineating variations in soil physical (bulk density, moisture content, and percentage clay), chemical (total and particulate organic matter, total C and N, extractable P, laboratory-measured electrical conductivity [$EC_{1:1}$] and pH), and biological (microbial biomass and potentially mineralizable N) properties that in turn impacted crop productivity in a study conducted in eastern Colorado.

Summary and conclusions

In summary, the corn hybrids used in this study responded similarly to field variability while plant density treatments responded differentially. Economically optimal plant densities changed by around 5000 plants ha^{-1} between high and low-yielding field areas, producing a potential savings in seed costs of \$6.25 ha^{-1}. While Bullock *et al.* (1998) observed differences in economically optimal plant densities as a function of yield potential in an extensive study in the Corn Belt region of the US, they concluded that variable rate seeding would be infeasible, because of high costs associated with characterizing site variability. We observed strong associations between yield variation and assessments of landscape attributes such as elevation, SB, and EC_a. Various combinations of the landscape attributes accounted for 47%, 95%, and 76% of the spatial variation in average grain yields for the 1997, -98, and -99 sites, respectively. These measurements appear to be an indirect assessment of important soil physical, chemical and biological properties known to have direct impact on crop productivity. Since indirect assessments are more convenient and likely more inexpensive than direct measures of soil properties, we offer them as a practical and perhaps economical means of delineating management zones, which could in turn serve as a template for variable application of plant densities. However, additional on-farm research may be required to further refine prescriptions for variable application of plant densities.

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