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# Delineating productivity zones on claypan soil fields using apparent soil electrical conductivity

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**Abstract**

Efficient and cost-effective methods are needed for delineating sub-field productivity zones to improve soil and crop site-specific management. This investigation was conducted to answer the question of whether apparent soil electrical conductivity ($EC_a$) and elevation could be used to delineate productivity zones (SPZ) for claypan soil fields that would agree with productivity zones delineated from yield map data (YPZ). Ten and seven years of combine-monitored yield maps were available for two Missouri claypan soil fields, designated Field 1 and Field 2, respectively. The fields were generally cropped in corn and soybean. Soil $EC_a$ data were collected with a non-contact, electromagnetic induction-based $EC_a$ sensor (Geonics EM38) and a coulter-based sensor (Veris model 3100). Elevation data were collected using a real-time kinematic GPS. Unsupervised fuzzy *c*-means clustering was independently used both on yield data to delineate three YPZ and on combinations of $EC_a$ and/or elevation data to delineate three SPZ. Outcomes of YPZ and SPZ were matched and agreement calculated with an overall accuracy statistic and a statistical index called the Kappa coefficient. Best performing combinations of $EC_a$ and elevation variables gave 60–70% agreement between YPZ and SPZ. We consider this level of agreement promising, especially considering that there were many other yield-limiting factors unrelated to $EC_a$ and elevation. Generally, multiple variables of $EC_a$ and

*Abbreviations:* CV, coefficient of variation; $EC_a$, apparent profile soil electrical conductivity; $EC_{a\text{-sh}}$, 0–30 cm depth $EC_a$ using a coulter-based sensor; $EC_{a\text{-dp}}$, 0–100 cm depth $EC_a$ using a coulter-based sensor; $EC_{a\text{-em}}$, 0–150 cm depth $EC_a$ using a electromagnetic-based sensor; MZA, Management Zone Analyst software; S.D., standard deviation; SPZ, $EC_a$ and/or elevation-based productivity zones; YPZ, yield productivity zones

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elevation were better than a single variable for generating SPZ. The specific combinations of $EC_a$ and/or elevation variables that gave highest agreement between YPZ and SPZ were field specific. Based on these findings, we conclude $EC_a$ and elevation measurements can be reliably used for creating productivity zones on claypan soil fields.
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*Keywords:* Management zones; Precision agriculture; Sensor; Site-specific crop management; Spatial pattern

## 1. Introduction

Somewhere between representing a single field as a single unit and representing the field as high-resolution continuous data lies the concept of *management zones*. Managing by spatial variation in soil and crop factors within the framework of management zones is intuitive for producers because it is a concept that allows them to visualize operations merely as breaking up large fields into smaller fields (Kitchen et al., 2002). Yet, the phrase "management zone" can imply multiple meanings and applications. Most commonly, the phrase is used to identify sub-field areas that vary in some management input or practice. However, if the same decision rule or algorithm is applied over an entire field and the zone is just a classified representation of this rule, minimal value may result. A more advanced and valuable approach is where each zone represents a unique algorithm or response curve. For example, the response of corn yield to N fertilizer may be different in a zone having a certain combination of topographic and soil characteristics than in some other zone. "Management zones" have also been used to delineate areas of a field for assessing the effects of soil and biotic factors on yield. More accurately, these could be referred to as "analysis zones." A derivation of this approach has been used to identify unique areas within fields for crop growth model simulation (Fraisse et al., 2001b). Thus, the phrase "management zone" is somewhat ambiguous without including additional information that clearly specifies the intended goal in sub-dividing the field.

Methods for delineating management zones vary widely in the information used as well as the techniques for creating the zone boundaries. Some examples include hand drawing polygons on yield maps and/or bare soil photos (Fleming et al., 2000), classification of soil or digital elevation data (MacMillan et al., 1998; van Alphen and Stoorvogel, 1998; Franzen et al., 2002), mulitvariate cluster analysis using yield map data (Lark, 1998; Boydell and McBratney, 1999; Jaynes et al., 2003; Ping and Dobermann, 2003), soil and landscape properties (Fraisse et al., 2001a; Burrough et al., 1992; McBratney and DeGruijter, 1992; Odeh et al., 1992), or remotely sensed images (Ahn et al., 1999; Boydell and McBratney, 1999), and identification of yield stability using temporal variance (Lark and Stafford, 1997; Whelan and McBratney, 2000).

A specific application of management zones is identification of areas of similar productivity potential, where the zones might more accurately be called "productivity zones" or "yield zones". Producer interest in identifying productivity zones is due to the fact that some key management decisions are dependent on reliable estimates of expected yield. A few examples include N fertilizer rate, seeding rate, and replacement of soil nutrients

based on crop removal (sometimes referred to as "maintenance" fertilization). In rainfed agriculture settings, productivity zones have been primarily related to accumulation and movement of water as affected by soil and the landscape (MacMillan et al., 1998; Jaynes et al., 2003). Complicating productivity zone identification in these settings are year-to-year climate variations. Highly productive areas of a field during "dry" years can be the low producing areas of the same field in "wet" years (Colvin et al., 1997; Sudduth et al., 1997). Productivity zones have most commonly been derived from an analysis of combine yield map data (Boydell and McBratney, 1999; Jaynes et al., 2003; Ping and Dobermann, 2003). Sawyer (1994) noted that if an analysis averages yield maps across wet and dry years, then the procedure may neutralize information needed to better understand the interaction between soil/landscape properties and climate and the resulting effects on crop production. Static soil and landscape factors have also been used to derive productivity zones (McBratney and DeGruijter, 1992; Odeh et al., 1992; Fraisse et al., 2001a). When compared to the use of multiple years yield maps, deriving productivity zones from soil and landscape information (which can be obtained from a single data collection event) represents a tremendous time savings and is, therefore, appealing to producers (Kitchen et al., 2002). Use of soil and landscape information to create productivity zones does assume a reasonable understanding of the agronomic effects of the soil and landscape information.

Apparent profile soil electrical conductivity ($EC_a$) provides an indirect measure of soil physical and chemical properties (McNeill, 1992; Rhoades et al., 1999), properties that can have a dominant influence on plant growth and yield (Jaynes et al., 1995; Lund et al., 2001; Zhang and Taylor, 2001; Kitchen et al., 2003). Characterization of soil variability can be improved by utilizing $EC_a$ measurements obtained from different types of $EC_a$ sensors (Sudduth et al., this issue). For claypan soils of the U.S. Midwest, $EC_a$ has been found to be highly correlated with topsoil thickness (i.e., depth to the Bt horizon) (Doolittle et al., 1994; Sudduth et al., 2001). This soil property causes variation in infiltration and water storage characteristics (Jamison et al., 1968) and is highly related to yield variation in crop growth years with average and below average precipitation (Kitchen et al., 1999). Previous analyses attempting to account for within-field yield variation were improved by including elevation with $EC_a$ measurements (Kitchen et al., 2003).

The existence of a significant relationship between mapped $EC_a$ and yield information advances the question of whether $EC_a$ could be the foundation for delineating productivity zones. An assessment of classified yield-mapped data obtained over multiple years for a few selected fields could help develop concepts of productivity zone delineation, that could then be extended to other fields, where $EC_a$ could quickly be measured, but have no history of yield monitoring. The objective of this research was to investigate the effectiveness of using soil $EC_a$ measurements (either alone or multiple $EC_a$ measurements taken from different sensors) for delineating productivity zones for claypan soils. Because of recent interest in using classification methods for creating "management zones", we were particularly interested in addressing this objective by comparing zones derived from classified yield data with zones classified from $EC_a$ measurements. A sub-objective was to determine if inclusion of relative field elevation along with $EC_a$ could improve productivity zone delineation.

Fig. 1. Research fields located in north-central Missouri.

## 2. Materials and methods

### 2.1. Sites description

Research sites were two claypan soil fields [Field 1 (latitude 39.2297, longitude −92.1169; 28 ha), and Field 2 (latitude 39.2346, longitude −92.1469; 13 ha)] approximately 2 km apart near the town of Centralia in north-central Missouri (Fig. 1). Claypan soils occupy about 4 million ha in Missouri and Illinois and are associated with Major Land Resource Area 113 (Soil Survey Laboratory Staff, 1992). Clay content in the argillic horizon is usually >500 g $kg^{-1}$ and is comprised of smectitic (high shrink–swell) clay minerals. These soils have a unique hydrology with slow water flow in the soil matrix of the clay layer when wet (i.e., winter and spring), but rapid preferential flow through cracks after profile drying (i.e., late summer and early fall) (Jamison et al., 1968).

Ten growing seasons (1993–2002) were evaluated for Field 1 and seven (1996–2002) growing seasons were evaluated for Field 2. The fields were cropped in a corn–soybean rotation, exceptions being grain sorghum (milo) grown 1 year on Field 1 and 2 consecutive years of soybean on Field 2. Field 1 was managed with minimum tillage (chisel plow and field cultivator) and Field 2 was managed with no-tillage. Growing-season precipitation during the years of this study is shown compared to the 58-year average (1940–1998) in Table 1.

### 2.2. Soil $EC_a$, elevation, and yield data collection

Soil $EC_a$ was measured in October 1999 using the Veris model 3100 sensor cart system manufactured by Veris Technologies of Salina, Kansas (Lund et al., 1999) and the EM38 manufactured by Geonics Limited, Mississauga, Ont., Canada (Geonics Limited, 1998).[1] The Veris sensor identifies soil variability by directly sensing $EC_a$. As the cart is pulled through the field, a pair of coulter electrodes transmit an electrical current into the soil, while two other pairs of coulter electrodes measure the voltage change, one pair for a "shallow" $EC_a$ reading (0–30 cm, designated here as $EC_{a\text{-sh}}$) and one pair for a "deep" $EC_a$ reading (0–100 cm, designated here as $EC_{a\text{-dp}}$). The EM38 is a lightweight bar approximately 1

[1] Mention of trade names or commercial products is solely for the purpose of providing specific information and does not imply recommendation or endorsement by the United States Department of Agriculture.

Table 1
Monthly growing-season precipitation (cm) for the fields in this study (1993–2002) compared to the 58-year average

| Year | April | May | June | July | August | September |
|---|---|---|---|---|---|---|
| 1993 | 14.5 | 8.6 | 14.2 | 16.2 | 13.2 | 36.0 |
| 1994 | 26.4 | 2.6 | 8.9 | 1.0 | 3.9 | 6.0 |
| 1995 | 13.7 | 25.7 | 17.3 | 7.4 | 16.8 | 7.3 |
| 1996 | 6.2 | 17.4 | 8.8 | 7.0 | 12.2 | 8.6 |
| 1997 | 8.2 | 12.6 | 9.9 | 4.0 | 9.1 | 5.6 |
| 1998 | 10.3 | 5.5 | 24.0 | 14.9 | 4.2 | 14.2 |
| 1999 | 17.5 | 8.6 | 14.0 | 0.9 | 3.4 | 3.1 |
| 2000 | 2.2 | 8.6 | 17.1 | 7.1 | 22.3 | 4.7 |
| 2001 | 11.5 | 18.5 | 15.4 | 8.9 | 2.1 | 5.0 |
| 2002 | 13.9 | 23.3 | 5.3 | 5.4 | 8.6 | 1.5 |
| 58-Year average | 8.9 | 10.8 | 10.8 | 9.0 | 8.9 | 9.2 |

m in length and includes calibration controls and a digital readout. $EC_a$ readings were output through a port and recorded on a computer. The EM38 was attached to a wheeled cart (Sudduth et al., 2001) and operated in the vertical dipole mode, providing an effective measurement depth of 0–150 cm (designated here as $EC_{a\text{-em}}$). A comparison of these two sensors over a range of soil types is provided elsewhere in this issue (Sudduth et al., this issue).

$EC_a$ data were collected on transects approximately 10 m apart on 1 s intervals, which corresponded to a measurement about every 2–3 m along the transects. All $EC_a$ measurements were georeferenced using DGPS receivers. Other details of the procedures used for $EC_a$ collection have been previously given (Kitchen et al., 2003; Sudduth et al., 2003). $EC_a$ readings were kriged following generally accepted geostatistical procedures using ArcGIS Geospatial Analyst. Data were investigated for trend and anisotropy. In datasets where underlying trends existed, universal kriging was used, otherwise, simple kriging was chosen. Anisotropic models were selected when non-stationarity was detected by rotating the lag azimuth. Best performing semi-variogram models were identified by eye and used for block kriging. A final 10 m × 10 m grid cell size was chosen because it reflects the scale of variability associated with the $EC_a$ measurements and the yield monitoring system data (discussed later). Elevation data was collected simultaneously with the $EC_a$ data using a real-time kinematic GPS (vertical accuracy approximately 3–5 cm). Elevation data were block kriged to the same 10 m grid as $EC_a$ data.

Combines equipped with commercially-available yield sensing systems were used to obtain grain yield. Yield data files were processed by removing individual data points where data were unreliable. Specifically, points were removed due to any one or a combination of the following factors: significant positional errors, abrupt changes in operating speed, significant ramping of grain flow when entering and leaving the crop, a partial swath width of crop entering the combine, and instantaneous yield values outside reasonable bounds. Precise threshold values for rejection were dependent upon the field, crop type, and individual combine/yield monitoring system used to collect each dataset. Using the previously described geostatistical procedures, appropriate semi-variogram models and pa-

rameters were used to krige the yield data to the same 10 m grid as $EC_a$ and elevation data. Thus, all analyses were conducted on the same 10 m grid. Excluded on Field 1 were some small uncropped areas (weather station and ground water monitoring well nests) as well as four <1 ha areas used for fertility response studies on the north-west portion of the field.

Each site-year was normalized by dividing the yield from each cell by the overall average yield from all the cells within that site-year. This field-average-normalized yield had a distribution with a mean of one and a theoretical range of zero to infinity, although in practice values ranged between 0.1 and 2.6. This normalizing procedure allowed comparison and averaging across variable climate and crop types.

### 2.3. Data processing and analysis

We desired to develop a quantitative procedure to compare the similarity of productivity management zone maps derived from two unique and independently classed data types; the first being yield productivity zones (YPZ) from mapped yield data, and the second being soil $EC_a$ and elevation-based productivity zones (SPZ). Such a comparison of independently classed maps to determine agreement is common in remote sensing studies (Jensen, 1996). Reasonable agreement would provide a rationale for using the more easily obtained data (i.e., $EC_a$ and elevation) to act as a surrogate for data that was more difficult, time-consuming, or expensive to obtain (i.e., yield).

A three-step process (Fig. 2) was employed for developing and comparing YPZ maps to SPZ maps. In Step 1, YPZ were identified using the average of all years' yield, and by the average after grouping years into "deficit", "optimal" or "excessive" precipitation years (explained in detail in Section 3). Delineation into YPZ was accomplished using a software program called Management Zone Analyst (MZA) (Fridgen et al.,2004). MZA uses a fuzzy *c*-means unsupervised clustering algorithm. Fuzzy *c*-means (also known as fuzzy *k*-means) uses a weighting exponent to control the degree to which membership sharing occurs between classes (Bezdek, 1981). Fuzzy *c*-means classification has been used for classifying soil and landscape data (Burrough et al., 1992; McBratney and DeGruijter, 1992; Odeh et al., 1992) and yield data (Lark and Stafford, 1997; Lark, 1998). Specific justification for the appropriateness in using this algorithm for classification of soil information has been documented (Odeh et al., 1992). MZA requires specifications of a number of clustering parameters. Settings used in MZA for our analyses were as follows: Euclidean measure of similarity for univariate clustering and Mahalanobis measure of similarity for mulitvariate clustering; fuzziness exponent = 1.3; maximum number of iterations = 300; convergence criterion = 0.0001; number of zones to extract = 3. Creation of only three zones was selected because our previous research on claypan fields found that little was gained by using more than three or four productivity zones (Fraisse et al., 2001a). Research on different soils also recommended the use of three to four classifications (Fleming et al., 2000; MacMillan et al., 1998).

In Step 2, 19 different combinations of the three $EC_a$ measurements and elevation (Table 2) were used as clustering variables within MZA to create maps having three SPZ. Ratios of $EC_a$ readings from the different sensors were included since they helped to explain field level variability in other research (Corwin et al., 1999). Parameter settings for

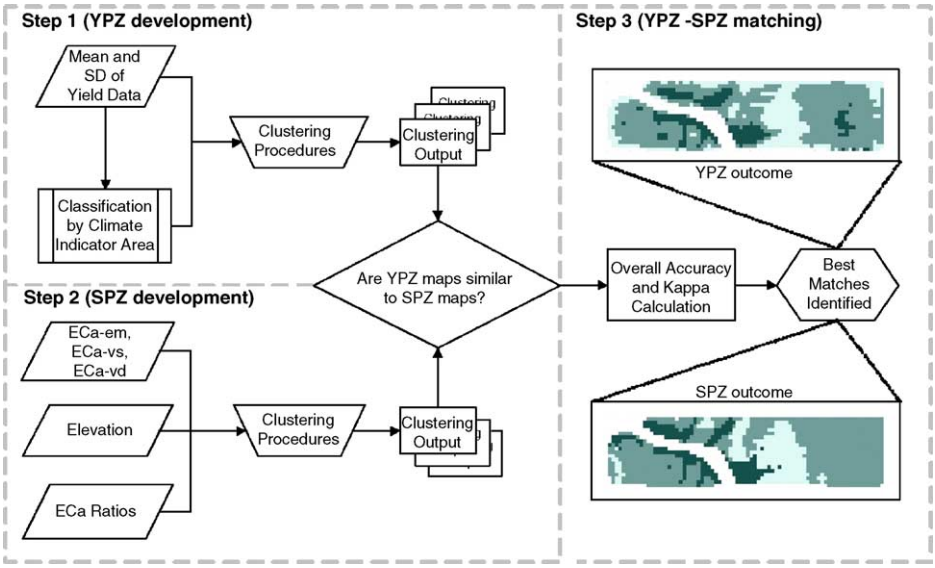



Fig. 2. Flowchart of analysis procedures.

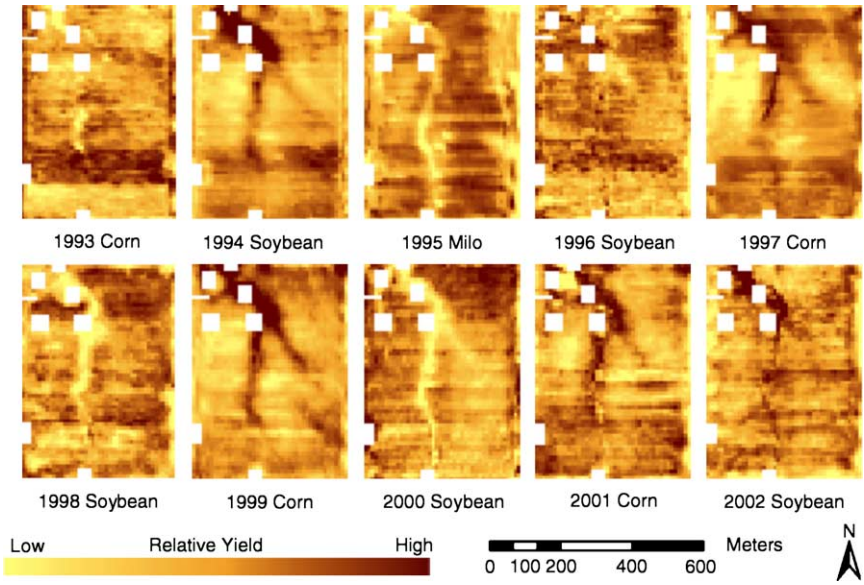



Fig. 3. Field 1 yearly-average-normalized yield maps over 10 years. Small areas excluded (shown as white blocks) were uncropped areas (weather station and ground water monitoring well nests) or four <1 ha areas used for fertility response studies on the north-west portion of the field.

Table 2
Listing of the soil EC and elevation variable combinations used in unsupervised clustering to delineate potential productivity zones

| | Variables used in clustering |
|---|---|
| 1 | $EC_{a\text{-}sh}$ |
| 2 | $EC_{a\text{-}dp}$ |
| 3 | $EC_{a\text{-}em}$ |
| 4 | Elevation |
| 5 | $EC_{a\text{-}sh}/EC_{a\text{-}dp}$ |
| 6 | $EC_{a\text{-}sh}/EC_{a\text{-}em}$ |
| 7 | $EC_{a\text{-}dp}/EC_{a\text{-}em}$ |
| 8 | $EC_{a\text{-}sh}$, elevation |
| 9 | $EC_{a\text{-}dp}$, elevation |
| 10 | $EC_{a\text{-}em}$, elevation |
| 11 | $EC_{a\text{-}sh}$, $EC_{a\text{-}dp}$ |
| 12 | $EC_{a\text{-}sh}/EC_{a\text{-}dp}$, elevation |
| 13 | $EC_{a\text{-}sh}/EC_{a\text{-}em}$, elevation |
| 14 | $EC_{a\text{-}dp}/EC_{a\text{-}em}$, elevation |
| 15 | $EC_{a\text{-}sh}$, $EC_{a\text{-}dp}$, $EC_{a\text{-}em}$ |
| 16 | $EC_{a\text{-}sh}/EC_{a\text{-}dp}$, $EC_{a\text{-}em}$ |
| 17 | $EC_{a\text{-}sh}$, $EC_{a\text{-}dp}$, elevation |
| 18 | $EC_{a\text{-}sh}/EC_{a\text{-}dp}$, elevation |
| 19 | $EC_{a\text{-}sh}$, $EC_{a\text{-}dp}$, $EC_{a\text{-}em}$, elevation |

clustering within MZA were the same as those described for yield. In Step 3, on a cell-by-cell basis YPZ maps (Step 1) were compared to SPZ maps (Step 2).

Two measures of classification agreement were used: (1) a simple overall accuracy statistic, and (2) a statistical index called the Kappa coefficient (Jensen, 1996). Overall accuracy was computed by dividing the number of correctly matched cells by the total number of cells in the dataset, yielding the fraction of total cells that are identically classified. The Kappa coefficient of agreement, a common index used for accuracy assessment in remote sensing, measures pair-wise agreement between the margin cells in a cross-classification contingency table, then correcting for chance agreement. As an example, a Kappa coefficient value of 0.82 would imply that the classification process was avoiding 82% of the errors that a completely random classification would generate. Kappa and overall accuracy values are greatest when spatial agreement of the two classifications is maximized. To objectively rank classification pairs, it was necessary to consider all possible combinations of YPZ paired to SPZ. Only the five SPZ outcomes that resulted in the highest Kappa coefficient were reported.

## 3. Results

The goal of this study was to test if $EC_a$ and elevation measurements could effectively be used to generate SPZ that agree with YPZ for claypan soils. The steps outlined in Fig. 2 also provide a structure for presenting the results. In Step 1, YPZ were derived from the multiple years of yield data using unsupervised clustering. Since these zones are based on empirical data, they become the “reference”. In Step 2, the same unsupervised clustering

procedure was used on combinations of $EC_a$ and elevation measurements to derive SPZ. In Step 3, the zones from the first two steps were compared by calculating measures of agreement.

### 3.1. Summary of yield information for two claypan soil fields

A total of 10 (1993–2002) and 7 (1996–2002) crop years of yield map information were available for Field 1 (Fig. 3) and Field 2 (Fig. 4), respectively. Yield descriptive statistics by site-year are shown in Table 3. The fields have generally been in a corn–soybean rotation. Exceptions were that grain sorghum replaced corn in 1995 on Field 1 and there were 2 years of continuous soybean (1998 and 1999) on Field 2. Since grain sorghum growth and physiology is comparable to corn, this dataset was grouped with corn for interpretation.

Within a field, variability in corn yield was generally higher than that of soybean yield, as indicated by coefficients of variation (CV; Table 3). We attribute the lower variability in soybean yield on claypan soil fields to this crop's characteristic indeterminate flowering and its resultant ability to respond to water deficiency stress. Past research has shown corn on claypan soils to be over five times more sensitive to water deficiency than soybean (Thompson et al., 1991).

Yield data was normalized to the field average of each year to allow for year-to-year and field-to-field comparisons (normalized minimum and maximum shown in Table 3). Although the magnitude of yield variation seemed to be crop specific, examination of normalized yield maps by year (Figs. 3 and 4) visually showed similar spatial yield patterns across many years. Because of this similarity, along with our intent to create YPZ applicable to multiple grain crops, we decided to include data from all crops in deriving the zones. The average yield CV for Field 1 corn was 14% and for soybean was 10%. Yield variability was considerably higher for Field 2 with average CV values of 29 and 20% for corn and soybean, respectively. We attribute these differences between fields to the degree and spatial extent of soil variation (explained more fully later).

### 3.2. Creating productivity zones with yield data (Step 1)

For Field 1, the 10-year average of normalized mean yields (Fig. 5a) was first used for generating YPZ. A second approach was to include the standard deviation (S.D.) of normalized mean yield over the 10 years (Fig. 5b) as a cluster variable along with the 10-year average yield. The intent of this second approach was to see if zones derived from $EC_a$ and elevation matched better when YPZ included a measure of temporal yield variation.

An alternative approach for taking into account temporal variability was also tested. Examination of the Field 1 yield maps over the 10 years (Fig. 3) indicated some landscape positions were very sensitive to the amount of growing-season rainfall. In years with average or below average precipitation, yield on the eroded back-slope position was depressed because of water deficiency stress. For these same years, yield was generally highest at the foot-slope position, which for this field also acts as a drainage channel for surface runoff. In wet years, the reverse was found. The foot-slope was depressed in yield because of excessive water and the side-slope yielded above average. This "flip-flop" of grain yield in humid environments has been noted by others (Colvin et al., 1997; Sudduth et al., 1997).

Table 3
Descriptive statistics of yield data over 10 years for Field 1 and 7 years for Field 2

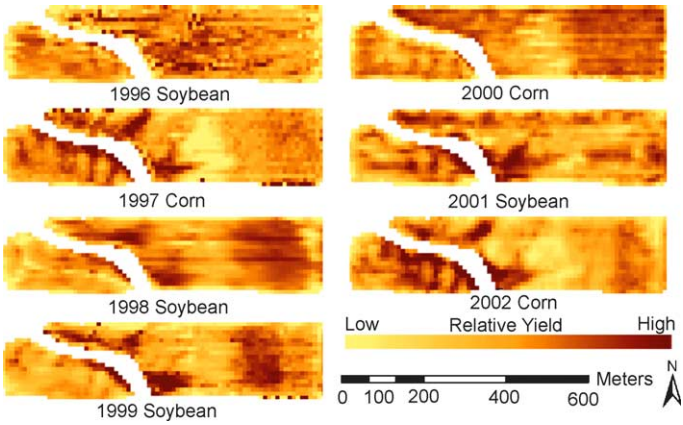
| Field | Crop | Year | Mean ($kg\,ha^{-1}$) | Minimum ($kg\,ha^{-1}$) | Maximum ($kg\,ha^{-1}$) | Normalized minimum | Normalized maximum | S.D. ($kg\,ha^{-1}$) | CV (%) |
|---|---|---|---|---|---|---|---|---|---|
| Field 1 | Corn | 1993 | 7348 | 4267 | 10330 | 0.58 | 1.41 | 785 | 11 |
| | Corn | 1997 | 7109 | 3030 | 9877 | 0.43 | 1.40 | 948 | 13 |
| | Corn | 1999 | 2591 | 971 | 5704 | 0.37 | 2.20 | 568 | 22 |
| | Corn | 2001 | 6103 | 3043 | 8215 | 0.50 | 1.35 | 680 | 11 |
| | Grain sorghum | 1995 | 5039 | 2618 | 6852 | 0.52 | 1.36 | 613 | 12 |
| | Soybean | 1994 | 1626 | 945 | 3395 | 0.58 | 2.09 | 291 | 18 |
| | Soybean | 1996 | 3069 | 1733 | 3565 | 0.56 | 1.16 | 299 | 6 |
| | Soybean | 1998 | 2107 | 1330 | 2604 | 0.63 | 1.24 | 167 | 8 |
| | Soybean | 2000 | 2600 | 1547 | 3326 | 0.60 | 1.28 | 231 | 9 |
| | Soybean | 2002 | 2012 | 760 | 3034 | 0.60 | 1.28 | 294 | 15 |
| Field 2 | Corn | 1997 | 6402 | 739 | 12343 | 0.12 | 1.93 | 2252 | 35 |
| | Corn | 2000 | 8898 | 4129 | 10879 | 0.46 | 1.22 | 1043 | 12 |
| | Corn | 2002 | 3280 | 584 | 8582 | 0.18 | 2.62 | 1264 | 39 |
| | Soybean | 1996 | 3029 | 435 | 6178 | 0.14 | 2.04 | 597 | 20 |
| | Soybean | 1998 | 2497 | 1110 | 3244 | 0.44 | 1.30 | 341 | 14 |
| | Soybean | 1999 | 1403 | 3117 | 282 | 0.20 | 2.22 | 471 | 34 |
| | Soybean | 2001 | 2453 | 758 | 3378 | 0.31 | 1.38 | 345 | 14 |

We hypothesized that these two sensitive landscape positions could be used to identify different types of climate years. To accomplish this, we delineated eroded side-slope and deposition foot-slope areas within a GIS and calculated the normalized mean yield within each of these sensitive areas (Fig. 5c–e). When the yield of both the foot-slope and the eroded side-slope was within 5% of the normalized field mean yield (i.e., >0.95 but <1.05), we classified those years as "optimal" in precipitation (Table 4). Three years fell into this category (1993, 1995, and 1996), and the average yield of these years is shown in Fig. 5d. When the yield of the foot-slope was ≤95% of the field mean, then those years were classified as "excessive" in precipitation. Fig. 5e shows the average yield of the 2 years (1998 and 2000) that fell into this category. When the yield of the eroded side-slope was ≤95% of the field mean, then those years were classified as "deficit" (1994, 1997, 1999, 2001, and 2002), and the average of these 5 years is shown in Fig. 5d. For this last class, yield of the foot-slope averaged 15% higher than the field mean. Thus, five different sets of YPZ were derived for Field 1 using the MZA unsupervised clustering. Yield productivity zones were created for the 10-year mean (Fig. 5a), 10-year S.D. (Fig. 5b), deficit-years mean (Fig. 5c), optimum-years mean (Fig. 5d), and excess-years mean (Fig. 5e).

Field 2 did not exhibit an equivalent sensitive soil area in the foot-slope where "excessive" moisture depressed yield. Near the uncropped grass waterway that divided the field into two separate cropped areas, foot-slope positions generally yielded well over all years because, unlike Field 1, these areas adequately drained excessive water following heavy rains. The eroded side-slope position on Field 2 was, however, sensitive to different precipitation years. In 1996, yield on the side-slope was similar to the rest of the field, following the "optimal" moisture classification given to Field 1 for that same year. With only 1 year in the "optimal" classification for Field 2, we chose to not create YPZ based on this year alone. In all other

Table 4
Mean normalized yields of the indicator landscape positions and resultant moisture classification

| Field | Year | Deposition foot-slope mean | Eroded side-slope mean | Moisture year classification |
|---|---|---|---|---|
| Field 1 | 1993 | 0.96 | 0.98 | Optimum |
| | 1994 | 1.22 | 0.80 | Deficit |
| | 1995 | 1.00 | 0.98 | Optimum |
| | 1996 | 0.99 | 1.01 | Optimum |
| | 1997 | 1.13 | 0.74 | Deficit |
| | 1998 | 0.89 | 0.98 | Excessive |
| | 1999 | 1.23 | 0.70 | Deficit |
| | 2000 | 0.86 | 1.03 | Excessive |
| | 2001 | 1.08 | 0.90 | Deficit |
| | 2002 | 1.08 | 0.93 | Deficit |
| Field 2 | 1996 | 1.26 | 1.16 | Optimal |
| | 1997 | 1.47 | 0.34 | Deficit |
| | 1998 | 1.16 | 0.95 | Deficit |
| | 1999 | 1.58 | 0.75 | Deficit |
| | 2000 | 0.98 | 0.92 | Deficit |
| | 2001 | 1.22 | 0.95 | Deficit |
| | 2002 | 1.47 | 0.45 | Deficit |



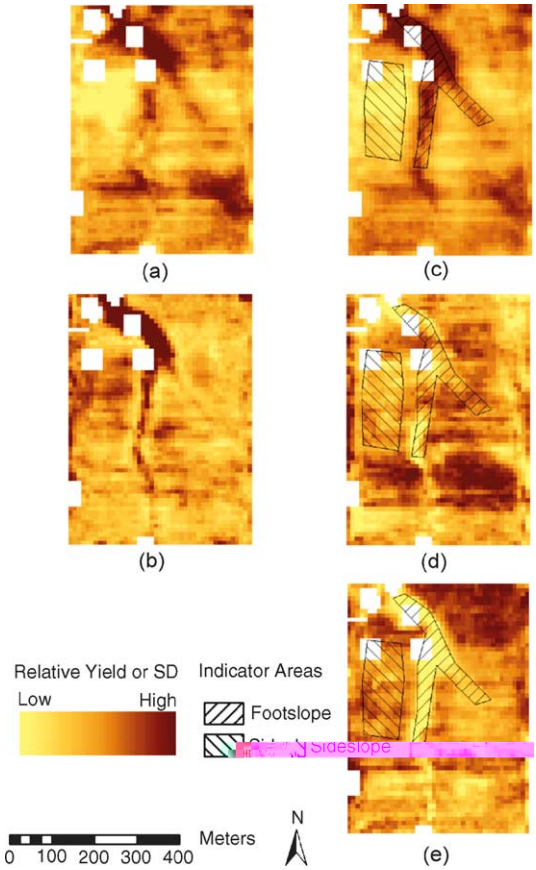


Fig. 4. Field 2 yearly-average-normalized yield maps over 7 years.