Available online at www.sciencedirect.com

SCIENCE DIRECT®

Computers and Electronics in Agriculture 46 (2005) 285–308

Computers and electronics in agriculture

www.elsevier.com/locate/compag

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

N.R. Kitchen[a,*], K.A. Sudduth[a], D.B. Myers[b], S.T. Drummond[a], S.Y. Hong[c]

[a] *USDA Agricultural Research Service, Cropping Systems and Water Quality Research Unit, 269 Agricultural Engineering Building, University of Missouri, Columbia, MO 65211, USA*

[b] *Soils Department, University of Missouri, Columbia, MO 65211, USA*

[c] *National Institute of Agricultural Science and Technology, Suwon, South Korea*

**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

* Corresponding author. Tel.: +1 573 882 1135; fax: +1 573 882 1115.
*E-mail address:* kitchenn@missouri.edu (N.R. Kitchen).

0168-1699/$ – see front matter. Published by Elsevier B.V.
doi:10.1016/j.compag.2004.11.012

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.
Published by Elsevier B.V.

*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.

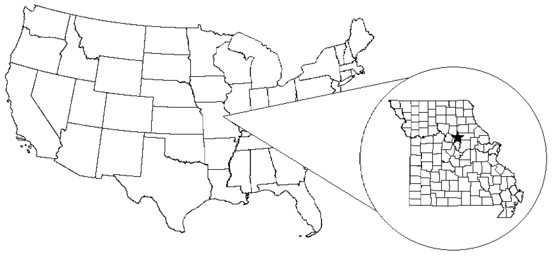


Fig. 1. Research fields located in north-central Missouri.

## 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 parameters 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

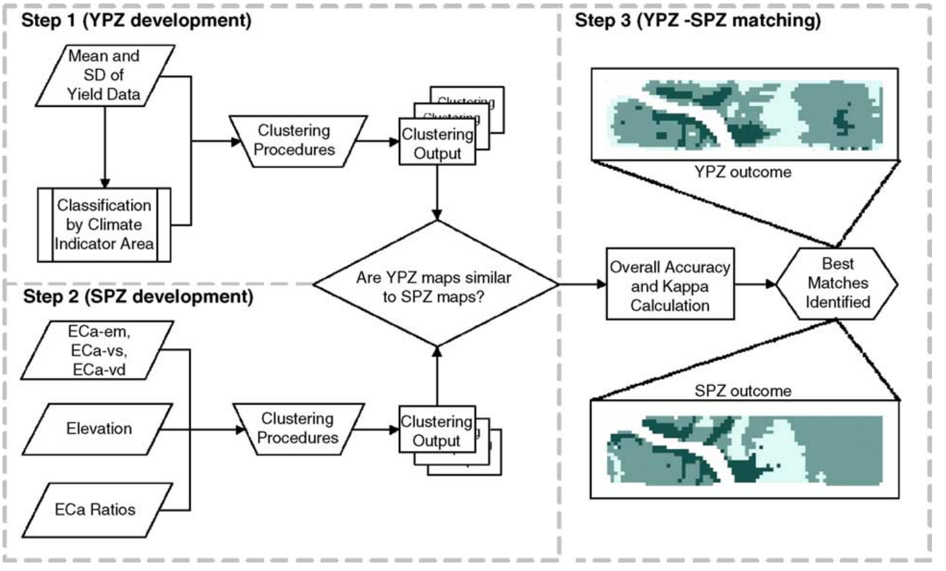



Fig. 2. Flowchart of analysis procedures.

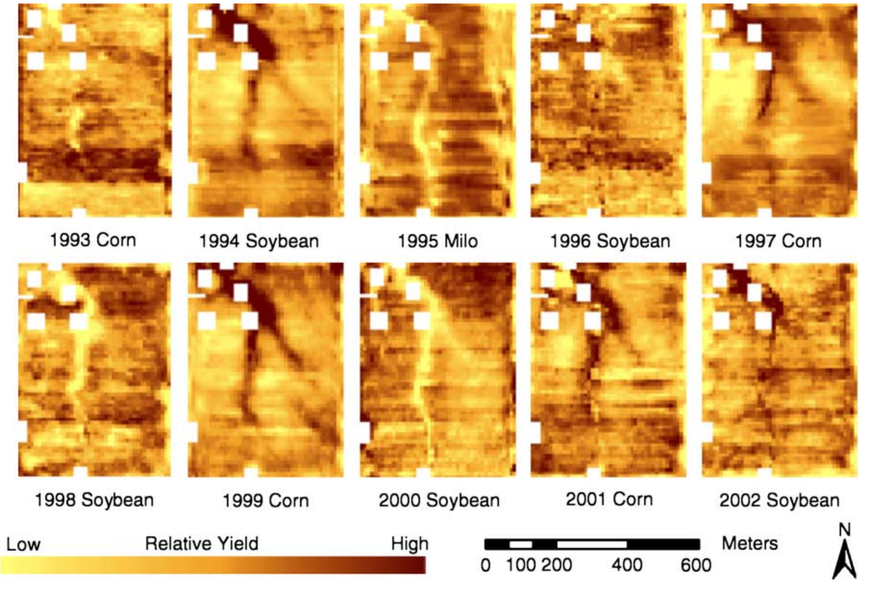



Fig. 3. Field 1 yearly-average-normalized yield maps over 10 years. Small areas excluded (shown as white blocks) were uncropped areas (weather station and ground water monitoring well nests) or four <1 ha areas used for fertility response studies on the north-west portion of the field.

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 |

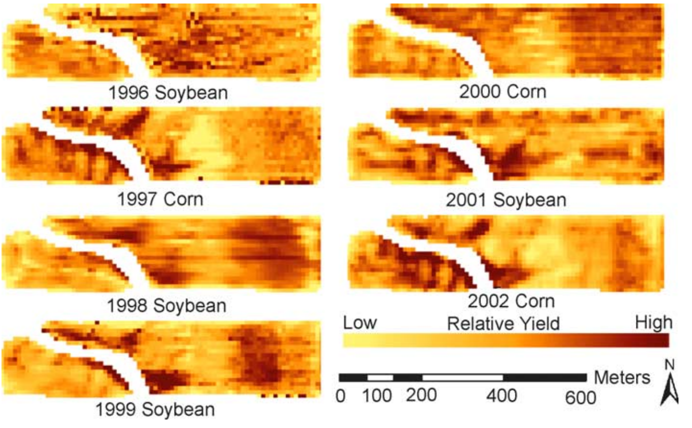
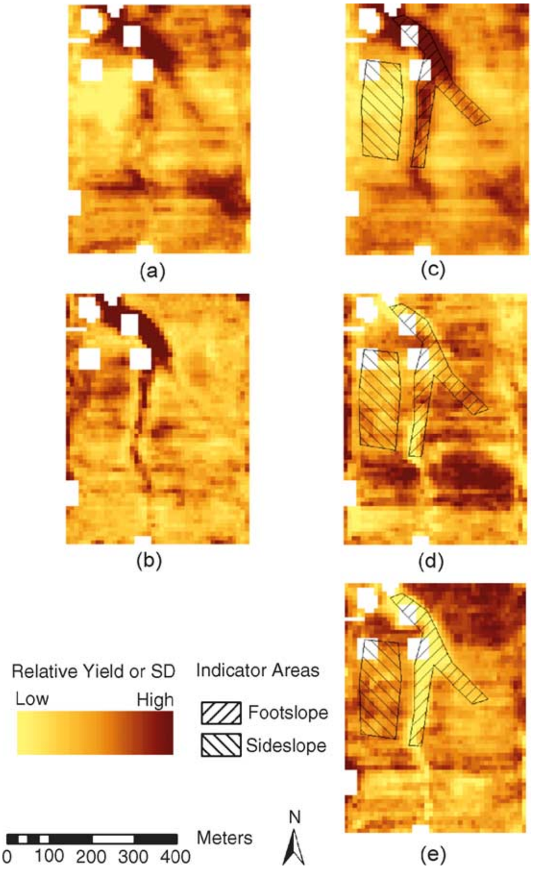



Fig. 4. Field 2 yearly-average-normalized yield maps over 7 years.



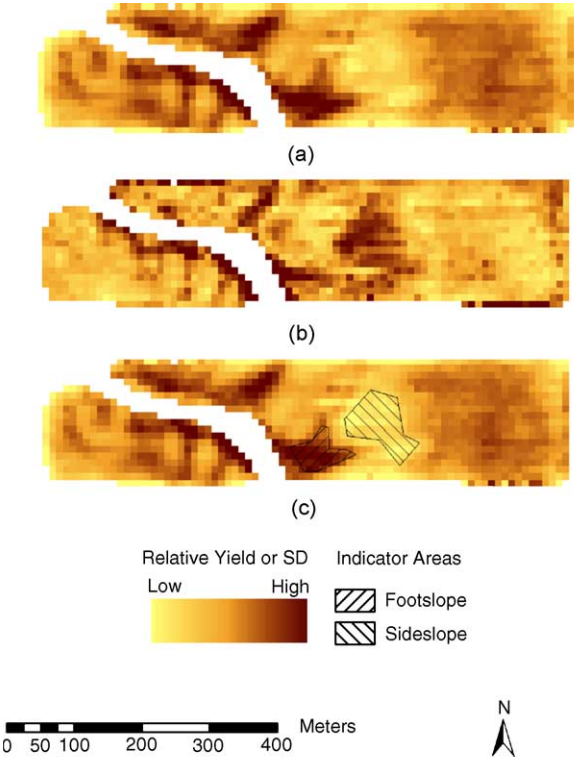



Fig. 6. Field 2 yield maps used for developing reference yield productivity zones (YPZ): (a) 7-year mean, (b) 7-year S.D., and (c) deficit-years mean.

years (1997–2002), the pattern of decreased yield on the sensitive eroded side-slope was evident (Table 4), and data from these years were averaged for a "deficit" year classification. Thus, MZA was used to develop three sets of YPZ for Field 2: (1) 7-year mean (Fig. 6a), (2) 7-year S.D. (Fig. 6b), and (3) deficit-years mean (Fig. 6c).

Growing-season precipitation expressed on a monthly basis (Table 1) did not necessarily always follow the classification by sensitive soil areas. As an example, an individual storm early in the season may have affected germination and stand, and yet precipitation the rest of the season may not have been excessive.

---

Fig. 5. Field 1 yield maps used for developing reference yield productivity zones (YPZ): (a) 10-year mean, (b) 10-year S.D., (c) deficit-years mean, (d) optimum-years mean, and (e) excess-years mean. 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.

### 3.3. Summary of $EC_a$ and elevation and creating SPZ (Step 2)

Maps of $EC_a$ and elevation are shown for Field 1 (Fig. 7) and Field 2 (Fig. 8), and the associated descriptive statistics are summarized in Table 5. Mean $EC_a$ measurements for Field 2 were notably greater than for Field 1 ($F$-test $P < 0.01$), as a result of higher maximum $EC_a$ values. The range in elevation of Field 2 is more than twice that of Field 1. Thus, the higher $EC_a$ from Field 2 can be attributed to steeper slopes (mean slope of 0.7% for Field 1 and 1.8% for Field 2) with the resulting erosion exposing the claypan horizon at the soil surface in some areas. Also, a larger proportion of Field 2 had high $EC_a$ values than did Field 1.

$EC_a$ for claypan soil fields is strongly related to the thickness of topsoil above the claypan horizon (Kitchen et al., 1999). Areas of lower $EC_a$ generally have over-washed sediment that has buried the claypan to a depth as much as 1.2 m below the soil surface. In contrast, areas of higher $EC_a$ are associated with the claypan near or at the soil surface. Plant-available water varies as a function of topsoil depth above the claypan and is a primary soil feature influencing crop yield (Kitchen et al., 1999; Thompson et al., 1991). Patterns of variation in $EC_a$ and yield are similar when visually comparing many of the yield maps of Figs. 3 and 4 with the $EC_a$ maps of Figs. 7 and 8.

Unsupervised classification using MZA was performed on 19 different combinations of $EC_a$ and elevation data (Table 2) to generate SPZ (Step 2 in Fig. 2).

### 3.4. Agreement between YZP and SPZ (Step 3)

The final step in the analysis (Step 3 in Fig. 2) matched all unique combinations of zones between the two independent classifications, calculated measures of agreement, and ranked the results. The $EC_a$ and/or elevation variable combinations generating SPZ clustering outcomes with the highest agreement to YPZ are reported (Table 6 for Field 1; Table 7 for Field 2).

Agreement between Field 1 YPZ and SPZ was generally lower than agreement values for Field 2 (no statistical test performed). One factor that likely contributed to lower agreement

Table 5
Descriptive statistics of EC and elevation data for the two study fields

| Field | Variable | $EC_{a\text{-sh}}$ (mS m$^{-1}$) | $EC_{a\text{-dp}}$ (mS m$^{-1}$) | $EC_{a\text{-em}}$ (mS m$^{-1}$) | Elevation |
|---|---|---|---|---|---|
| Field 1 | Mean | 9.9 | 20.0 | 30.0 | 263.6 |
| | Minimum | 4.2 | 5.2 | 20.6 | 261.9 |
| | Maximum | 22.7 | 46.0 | 42.9 | 264.8 |
| | S.D. | 2.6 | 7.7 | 3.0 | 0.6 |
| | CV | 26.4 | 38.4 | 10.0 | 0.2 |
| Field 2 | Mean | 16.4 | 25.9 | 35.8 | 261.9 |
| | Minimum | 7.3 | 7.1 | 19.6 | 257.8 |
| | Maximum | 40.2 | 57.7 | 59.2 | 265.0 |
| | S.D. | 6.7 | 10.0 | 5.7 | 2.2 |
| | CV | 40.5 | 38.7 | 15.9 | 0.8 |

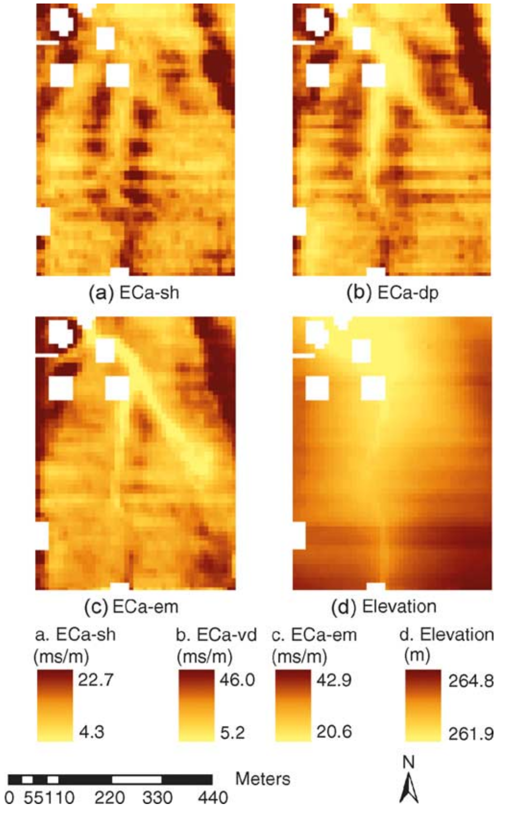



Fig. 7. Field 1 $EC_a$ and elevation maps: (a) $EC_{a\text{-sh}}$, (b) $EC_{a\text{-dp}}$, (c) $EC_{a\text{-em}}$, and (d) elevation. Small areas excluded (shown as white blocks) were uncropped areas (weather station and ground water monitoring well nests) or four <1 ha areas used for fertility response studies on the north-west portion of the field.

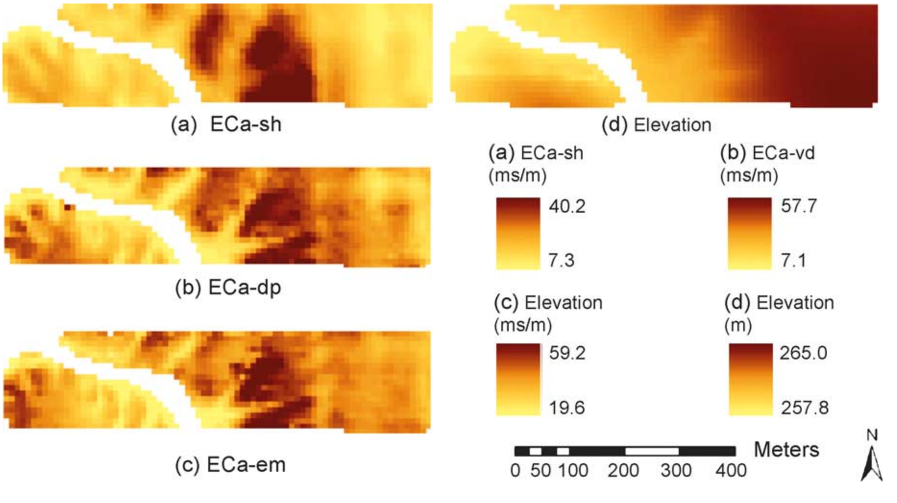



Fig. 8. Field 2 $EC_a$ and elevation maps: (a) $EC_{a\text{-sh}}$, (b) $EC_{a\text{-dp}}$, (c) $EC_{a\text{-em}}$, and (d) elevation.

values for Field 1 is the influence of historic management practices on yield variability. A series of archived aerial photos obtained from the USDA Farm Service Agency show that Field 1 was managed from the 1930s through the 1980s as smaller 6–8 ha fields running in an east–west direction. Grid soil sampling for nutrient and pH mapping substantiates soil differences coincident with the boundaries observed in the aerial photos (unpublished data). While the 31 ha Field 1 has been uniformly managed as one field since 1990, yield mapping has demonstrated that it is likely these soil differences associated with these historic management boundaries continue to influence yield. Abrupt yield changes running north–south provide evidence of the impact of historic management practices (especially obvious in 1993, 1994, 1996–1998, 2001, and 2002 yield maps of Fig. 3). Similar but more subtle east–west streaking patterns can also be seen in the $EC_a$ and elevation maps (Fig. 7).

Including some measure of temporal variation, either by adding yield standard deviation as a cluster variable or by using sensitive soil areas to sort and average by types of precipitation years, only slightly improved the measures of agreement for both fields (Tables 5 and 6). Zones generated by $EC_a$ and elevation had the highest agreement with

Table 6
Spatial agreement between Field 1 YPZ and SPZ from unsupervised cluster analysis

| Yield zone cluster variable(s) | Soil zone cluster variable(s) | Overall accuracy | Kappa coefficient |
|---|---|---|---|
| 10-Year mean | $EC_{a\text{-}sh}$, $EC_{a\text{-}dp}$, elevation | 0.54 | 0.25 |
| | $EC_{a\text{-}dp}$, elevation | 0.53 | 0.24 |
| | Elevation | 0.51 | 0.22 |
| | $EC_{a\text{-}sh}/EC_{a\text{-}dp}$, elevation | 0.54 | 0.22 |
| | $EC_{a\text{-}dp}/EC_{a\text{-}em}$, elevation | 0.52 | 0.21 |
| 10-Year S.D. | $EC_{a\text{-}sh}$, $EC_{a\text{-}dp}$, elevation | 0.56 | 0.26 |
| | $EC_{a\text{-}dp}$, elevation | 0.56 | 0.25 |
| | $EC_{a\text{-}sh}/EC_{a\text{-}dp}$, elevation | 0.58 | 0.23 |
| | $EC_{a\text{-}sh}/EC_{a\text{-}dp}$, | 0.52 | 0.22 |
| | Elevation | 0.53 | 0.21 |
| Deficit-years mean | $EC_{a\text{-}sh}$, $EC_{a\text{-}dp}$, elevation | 0.60 | 0.34 |
| | $EC_{a\text{-}sh}/EC_{a\text{-}dp}$, elevation | 0.60 | 0.31 |
| | $EC_{a\text{-}dp}$, elevation | 0.58 | 0.31 |
| | Elevation | 0.56 | 0.30 |
| | $EC_{a\text{-}dp}/EC_{a\text{-}em}$, elevation | 0.58 | 0.29 |
| Optimal-years mean | $EC_{a\text{-}dp}$ | 0.46 | 0.11 |
| | $EC_{a\text{-}sh}/EC_{a\text{-}em}$ | 0.43 | 0.10 |
| | $EC_{a\text{-}em}$, elevation | 0.41 | 0.09 |
| | $EC_{a\text{-}sh}/EC_{a\text{-}dp}$, elevation | 0.44 | 0.08 |
| | $EC_{a\text{-}sh}$ | 0.42 | 0.07 |
| Excess-years mean | $EC_{a\text{-}sh}$, $EC_{a\text{-}dp}$, elevation | 0.52 | 0.22 |
| | $EC_{a\text{-}dp}$, elevation | 0.52 | 0.22 |
| | $EC_{a\text{-}sh}/EC_{a\text{-}dp}$, elevation | 0.53 | 0.20 |
| | $EC_{a\text{-}em}$, elevation | 0.49 | 0.20 |
| | $EC_{a\text{-}dp}/EC_{a\text{-}em}$, elevation | 0.51 | 0.18 |

Of the 19 combinations of soil EC and elevation considered (see Table 2), only the five with the highest Kappa coefficient for each yield reference map are reported.

Table 7
Spatial agreement between Field 2 YPZ and SPZ from unsupervised cluster analysis

| Yield zone cluster variable(s) | Soil zone cluster variable(s) | Overall accuracy | Kappa coefficient |
|---|---|---|---|
| 7-Year mean | $EC_{a\text{-}sh}/EC_{a\text{-}dp}$, $EC_{a\text{-}em}$ | 0.68 | 0.43 |
| | $EC_{a\text{-}em}$ | 0.65 | 0.40 |
| | $EC_{a\text{-}dp}$, elevation | 0.57 | 0.36 |
| | $EC_{a\text{-}em}$, elevation | 0.58 | 0.33 |
| | $EC_{a\text{-}sh}$, $EC_{a\text{-}dp}$, $EC_{a\text{-}em}$ | 0.57 | 0.33 |
| 7-Year S.D. | $EC_{a\text{-}sh}/EC_{a\text{-}dp}$, $EC_{a\text{-}em}$ | 0.71 | 0.45 |
| | $EC_{a\text{-}em}$ | 0.66 | 0.41 |
| | $EC_{a\text{-}sh}$, $EC_{a\text{-}dp}$ | 0.59 | 0.34 |
| | $EC_{a\text{-}sh}$, $EC_{a\text{-}dp}$, $EC_{a\text{-}em}$ | 0.59 | 0.34 |
| | $EC_{a\text{-}dp}$ | 0.57 | 0.32 |
| Deficit-years mean | $EC_{a\text{-}sh}/EC_{a\text{-}dp}$, $EC_{a\text{-}em}$ | 0.72 | 0.49 |
| | $EC_{a\text{-}em}$ | 0.67 | 0.42 |
| | $EC_{a\text{-}sh}$, $EC_{a\text{-}dp}$ | 0.61 | 0.36 |
| | $EC_{a\text{-}dp}$ | 0.59 | 0.36 |
| | $EC_{a\text{-}dp}$, elevation | 0.58 | 0.36 |

Of the 19 combinations of soil EC and elevation considered (see Table 2), only the five with the highest Kappa coefficient for each yield reference map are reported.

reference yield zones derived from the “deficit” precipitation years. As might be anticipated, Field 1 crop years that exhibited “optimal” precipitation produced the lowest measures of agreement, and visually showed the least spatial similarity.

For Field 1, SPZ developed using a combination of $EC_{a\text{-}sh}$, $EC_{a\text{-}dp}$, and elevation variables agreed best with reference YPZ (the exception being “optimal” years and here agreement values were the lowest). Other combinations including the variables $EC_{a\text{-}dp}$ or $EC_{a\text{-}sh}/EC_{a\text{-}dp}$ were nearly as good. Top performing soil cluster combinations nearly always included the elevation variable. Elevation alone was almost as good a variable for creating SPZ on this field as it was in combination with $EC_a$ variables.

Field 2 SPZ created using $EC_{a\text{-}sh}/EC_{a\text{-}dp}$ and $EC_{a\text{-}em}$ had the highest agreement with YPZ (Table 7). This combination was slightly better than using $EC_{a\text{-}em}$ alone, and notably higher than any of the other top performing variable combinations. Elevation was much less useful for creating SPZ for Field 2 than it was for Field 1. We attribute this finding to excessive water ponding in lower elevation areas of Field 1, causing crop stand problems. Surface water drained well from Field 2 so ponding was not a problem.

In Figs. 9 and 10, the YPZ maps are shown alongside maps of the top performing SPZ maps. The patterns of the paired productivity maps were visually similar, particularly when overall accuracy was about 0.60 or greater. However, visual differences were obvious even for the paired maps with the highest agreement. For example, in Field 1 the most productive zone derived from yield information was a much smaller area than the coinciding zone derived from $EC_a$ and elevation (compare the “deficit” years mean map to the matched $EC_a$ and elevation map). Some field characteristics obvious in YPZ were not distinguished with zones from $EC_a$ and elevation data. As an example, the perimeter of Field 2 often fell into the low-yielding class for the YPZ. While some field edge yield data were removed in the

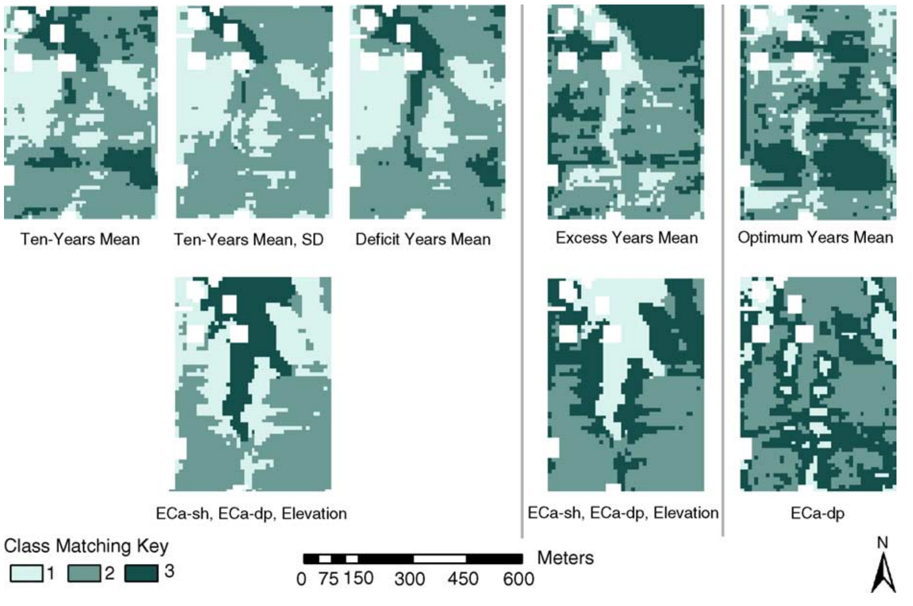



Fig. 9. Field 1 reference yield productivity zone maps (top) compared to the best performing productivity zone maps derived from unsupervised clustering of $EC_a$ and elevation (bottom). Yield by zones given in Table 8. Small areas excluded (shown as white blocks) were uncropped areas (weather station and ground water monitoring well nests) or four <1 ha areas used for fertility response studies on the north-west portion of the field.

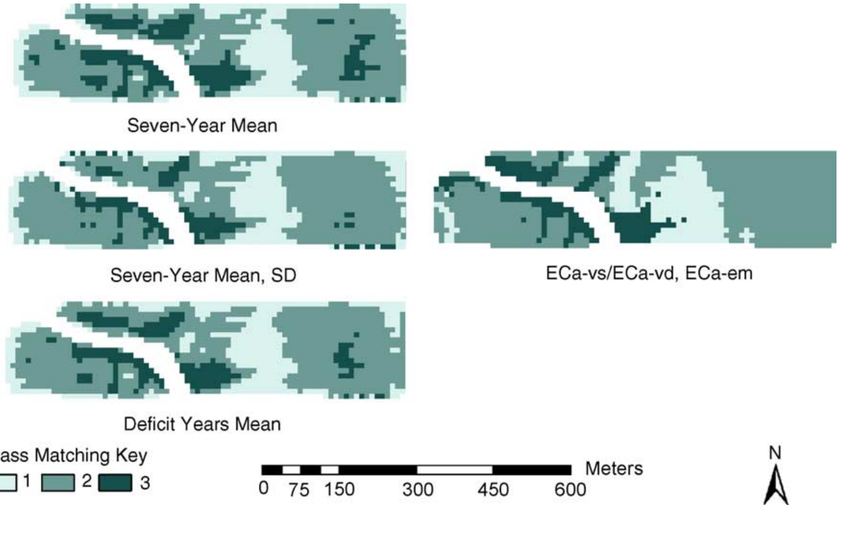



Fig. 10. Field 2 reference yield productivity zone maps (left) compared to the best performing productivity zone map derived from unsupervised clustering of $EC_a$ and elevation (right). Yield by zones given in Table 8.

Table 8
Mean normalized yield for YPZ and for the corresponding SPZ

| Field | Yield-based productivity zones | | | Soil-based productivity zones | | |
|---|---|---|---|---|---|---|
| | Cluster variable(s) | Zone | Mean | Cluster variable(s) | Zone | Mean |
| Field 1 | 10-Year mean | 1 | 0.92 | $EC_{a\text{-}sh}$, $EC_{a\text{-}dp}$, elevation | 1 | 0.96 |
| | | 2 | 0.99 | | 2 | 0.99 |
| | | 3 | 1.07 | | 3 | 1.03 |
| | 10-Year S.D. | 1 | 0.93 | $EC_{a\text{-}sh}$, $EC_{a\text{-}dp}$, elevation | 1 | 0.96 |
| | | 2 | 1.01 | | 2 | 0.99 |
| | | 3 | 1.11 | | 3 | 1.03 |
| | Deficit-years mean | 1 | 0.85 | $EC_{a\text{-}sh}$, $EC_{a\text{-}dp}$, elevation | 1 | 0.91 |
| | | 2 | 1.00 | | 2 | 0.99 |
| | | 3 | 1.19 | | 3 | 1.08 |
| | Optimal-years mean | 1 | 0.92 | $EC_{a\text{-}dp}$ | 1 | 0.99 |
| | | 2 | 0.99 | | 2 | 1.00 |
| | | 3 | 1.06 | | 3 | 1.01 |
| | Excess-years mean | 1 | 0.88 | $EC_{a\text{-}sh}$, $EC_{a\text{-}dp}$, elevation | 1 | 0.95 |
| | | 2 | 0.97 | | 2 | 0.98 |
| | | 3 | 1.05 | | 3 | 1.01 |
| Field 2 | 7-Year mean | 1 | 0.78 | $EC_{a\text{-}sh}/EC_{a\text{-}dp}$, $EC_{a\text{-}em}$ | 1 | 0.83 |
| | | 2 | 1.03 | | 2 | 1.01 |
| | | 3 | 1.23 | | 3 | 1.20 |
| | 7-Year S.D. | 1 | 0.79 | $EC_{a\text{-}sh}/EC_{a\text{-}dp}$, $EC_{a\text{-}em}$ | 1 | 0.83 |
| | | 2 | 1.04 | | 2 | 1.01 |
| | | 3 | 1.24 | | 3 | 1.20 |
| | Deficit-years mean | 1 | 0.76 | $EC_{a\text{-}sh}/EC_{a\text{-}dp}$, $EC_{a\text{-}em}$ | 1 | 0.83 |
| | | 2 | 1.04 | | 2 | 1.01 |
| | | 3 | 1.28 | | 3 | 1.20 |

Results are provided for only the outcomes with the highest agreement, as shown in Figs. 9 and 10.

yield cleaning process, this low-yielding edge effect on Field 2 remained and was due to large trees bordering much of the field.

When comparing the within-zone average-normalized yield for the paired zones, the reference yield zone with the lowest productivity (Zone 1) always exhibited lower yields than the equivalent zone generated using $EC_a$ and/or elevation (Table 8). Similarly, the reference yield zone with the highest productivity (Zone 3) always exhibited higher yields than the equivalent zone generated using $EC_a$ and/or elevation.

## 4. Discussion

Many might contend that a database of multiple years of yield maps would be a reliable source for generating productivity management zones. Yet, significant questions accompany this approach. How many years of maps are needed to represent long-term climate trends? Are the productivity patterns between different crops sufficiently similar to group for analysis? How does one consider year-to-year changes in management practices? Has the yield monitoring system been regularly calibrated for optimal performance and suspected erroneous yield data removed to provide quality maps? Might modern crop varieties with new genetics perform differently than varieties of the past? The sum of all these considerations represents for the producer considerable time and expense, and perhaps still a degree of uncertainty for how to proceed to delineate productivity management zones.

In contrast, soil properties that characterize infiltration, plant-available water storage, and rooting conditions are usually temporally stable, but can be quite variable spatially. These properties are a reflection of how soils form. Thus, others may argue that productivity management zones should rely on measurements that characterize these aspects of the soil. Yet even here, some management activities (e.g., compaction, no-tillage) can alter these properties over the course of years. The bigger issue has been finding an easy-to-obtain and low-cost method (or methods) of soil and landscape measurements to provide quality information about these properties. Apparent soil electrical conductivity is a reasonable candidate because yield and $EC_a$ have been shown to be related under conditions of rainfed cropping (Jaynes et al., 1995; Kitchen et al., 2003; Lund et al., 2001). We tested whether SPZ from easily obtained $EC_a$ and elevation measurements would be similar to YPZ created from the more difficult, time-consuming, and expensive yield-mapped data.

Two contrasting data types (yield and $EC_a$/elevation), independently classed, produced surprisingly good agreement; even in light of three clear factors. One, the sensors and methods used to obtain these two types of data are very dissimilar. The effects of the harvesting combine as it cuts, cleans, and transports the grain to the storage bin result in yield data from the monitoring system that is a moving average of yield rather than a spatially discrete measurement. While usually less spatially-dense than yield data, raw $EC_a$ and elevation data represent specific points on the field. Thus, these two data types have different levels of spatial precision. Two, even though adjacent grid cells were spatially dependent for both yield and $EC_a$ (semi-variogram range of influence >30 m), spatial location was not considered in the analysis. We theorize agreement between the two different types of productivity zones would have improved had we included some measure of location in the clustering process. Another proven approach that would introduce a spatial factor would be to apply an image-processing technique such as a “moving window” post-classification filter to reclassify individual or small groups of isolated cells, creating more contiguous productivity classes (Ping and Dobermann, 2003). This type of procedure would smooth the “pixelated” productivity zone maps in Figs. 9 and 10, ultimately improving overall accuracy and Kappa measures. Three, and perhaps most importantly, yield variability within fields is a function of much more than those soil properties represented by $EC_a$ and elevation. Numerous other soil (e.g., fertility, organic matter, temperature), biotic (weeds, insects, diseases), climatic (e.g., humidity, temperature, solar radiation), and management influences (e.g., skipped or run-over rows, field boundary treelines, historic variations in management) contribute in varying degrees to within-field yield variability. In the future, process-based crop models that accurately simulate numerous and interacting soil, climate, and management factors could be the means by which management zones are delineated (Jones et al., 2003).

In comparing the two fields, Field 2 was a better candidate for creating $EC_a$ based productivity zones. Variation in $EC_a$ measurements was greater and other prominent yield-controlling factors (i.e., historical management) were less obvious when compared to Field 1. We find intriguing the combination of $EC_{a\text{-sh}}/EC_{a\text{-dp}}$ and $EC_{a\text{-em}}$ as this study's best performing group of classifying variables (Field 2), and deserving of additional investigation. Another study has demonstrated that each of these $EC_a$ measurements provides unique information in characterizing soil variability (Sudduth et al., 2003).

For Field 1, we believe the influence of elevation on yield explained why the top performing $EC_a$ and elevation cluster group was the same for both "deficit" and "excess" years. Foot-slope areas with poor surface drainage showed stand and disease problems during wet periods, but have deep topsoil that prevents water stress in dry periods. Only minor improvement was achieved by including temporal variation (S.D. or sorting years by sensitive soil areas before clustering). More importantly, on each field, the best zone delineation for "deficit" years used the same set of $EC_a$ and elevation variables as the zone delineation for all years combined. We interpret this to mean that if the years of this study are representative of longer-term climate trends, water deficiency will have a dominant effect on yield variability, and this characteristic should be considered when delineating productivity zones for claypan soil fields.

## 5. Conclusions

Two Missouri claypan soil fields were investigated to answer the question of whether $EC_a$ and/or elevation sensor data could be used to delineate zones that would be similar to zones delineated from multiple years of yield maps. Our procedure treated both data types independently in the zone delineation process. 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 the fact that there exist many other yield-limiting factors unrelated to the soil properties that affect $EC_a$ and elevation. Multiple $EC_a$ and elevation variables used to generate SPZ agreed better with YPZ for both fields. Combinations of $EC_a$ and/or elevation variables that gave highest agreement between YPZ and SPZ were field specific. Contrasting results from the two fields indicated specific field characteristics need to be taken into account when developing productivity zones. Field 1's history of being managed prior to 1990 as a group of smaller fields seems to have caused soil differences that impact yield variability more than a decade later.

Claypan soils have been referred to by farmers as "droughty" soils. Half of the years in this dataset showed yield spatial variability caused by moisture deficiency. Because of the heavy weighting from "deficit" moisture years, creating YPZ with only these years did not alter the combination of $EC_a$ and elevation variables that performed best as a surrogate estimator of YPZ using all years. Additionally, the relationship of $EC_a$ and elevation measurements to properties affecting plant-available water and landscape hydrology are most likely the cause of the similarity between YPZ and SPZ. Based on these findings, we conclude $EC_a$ and elevation measurements can be reliably used for creating productivity zones on claypan soil fields.

## Acknowledgments

We thank the following for financial support for this research: North-Central Soybean Research Program and the United Soybean Board; USDA-CSREES *National Research Initiative* and *Special Water Quality Grants* programs; The Foundation for Agronomic Research. We thank M.R. Volkmann, R.L. Mahurin, H.L. Palm, and M.J. Krumpelman for their assistance in collecting field and crop measurements. We also acknowledge Don Collins and the late Bill Gvillo for their cooperation in allowing us to conduct investigations on their fields.

## References

Ahn, C.W., Baumgardner, M.F., Biehl, L.L., 1999. Delineation of soil variability using geostatistics and fuzzy clustering analyses of hyperspectral data. Soil Sci. Soc. Am. J. 63, 142–150.

Bezdek, J.C., 1981. Pattern Recognition with Fuzzy Objective Function Algorithms. Plenum Press, New York.

Boydell, B., McBratney, A.B., 1999. Identifying potential within-field management zones from cotton yield estimates. In: Stafford, J.V. (Ed.), Precision Agriculture '99. Proceedings of the Second European Conference on Precision Agriculture. Denmark, 11–15 July 1999. SCI, London, UK, pp. 331–341.

Burrough, P.A., Macmillan, R.A., VanDeursen, W., 1992. Fuzzy classification methods for determining land suitability from soil profile observations and topography. J. Soil Sci. 43, 193–210.

Colvin, T.S., Jaynes, D.B., Karlen, D.L., Laird, D.A., Ambuel, J.R., 1997. Yield variability within a central Iowa field. Trans. ASAE 40, 883–889.

Corwin, D.L., Carrillo, M.L.K., Vaughan, P.J., Rhoades, J.D., Cone, D.G., 1999. Evaluation of a GIS-linked model of salt loading to groundwater. J. Environ. Qual. 28, 471–480.

Doolittle, J.A., Sudduth, K.A., Kitchen, N.R., Indorante, S.J., 1994. Estimating depths to claypans using electromagnetic induction methods. J. Soil Water Conserv. 49, 572–575.

Fleming, K.L., Westfall, D.G., Wiens, D.W., Brodah, M.C., 2000. Evaluating farmer developed management zone maps for variable rate fertilizer application. Precision Agric. 2, 201–215.

Fraisse, C.W., Sudduth, K.A., Kitchen, N.R., 2001a. Delineation of site-specific management zones by unsupervised classification of topographic attributes and soil electrical conductivity. Trans. ASAE 44, 155–166.

Fraisse, C.W., Sudduth, K.A., Kitchen, N.R., 2001b. Calibration of the Ceres-Maize model for simulating site-specific crop development and yield on claypan soils. Appl. Eng. Agric. 17, 547–556.

Franzen, D.W., Hopkins, D.H., Sweeney, M.D., Ulmer, M.K., Halvorson, A.D., 2002. Evaluation of soil survey scale for zone development of site-specific nitrogen management. Agron. J. 94, 381–389.

Fridgen, J.J., Kitchen, N.R., Sudduth, K.A., Drummond, S.T., Wiebold, W.J., Fraisse, C.W., 2004. Management Zone Analyst (MZA): software for sub-field management zone delineation. Agron. J. 96, 100–108.

Geonics Limited, 1998. EM38 Ground Conductivity Meter Operating Manual, May 1998. Mississauga, Ont., Canada.

Jamison, V.C., Smith, D.D., Thornton, J.F., 1968. Soil and water research on a claypan soil. USDA-ARS Technical Bulletin 1379, U.S. Government Printing Office, Washington, DC.

Jaynes, D.B., Kasper, T.C., Colvin, T.S., James, D.E., 2003. Cluster analysis of spatiotemporal corn yield patterns in an Iowa field. Agron. J. 95, 574–586.

Jaynes, D.B., Colvin, T.S., Ambuel, J., 1995. Yield mapping by electromagnetic induction. In: Robert, P.C., Rust, R.H., Larson, W.E. (Eds.), Site-Specific Management for Agricultural Systems. Proceedings of the Second International Conference. Minneapolis, MN, 27–30 March 1995. ASA, CSSA, and SSSA, Madison, WI, pp. 383–394.

Jensen, J.R., 1996. Introductory digital image processing: a remote sensing perspective. Prentice-Hall, Upper Saddle River, NJ, pp. 250–251.

Jones, J.W., Hoogenboom, G., Porter, C.H., Boote, K.J., Batchelor, W.D., Hunt, L.A., Wilkens, P.W., Singh, U., Gijsman, A.J., Ritchie, J.T., 2003. The DSSAT cropping system model. Eur. J. Agron. 18, 235–265.

Kitchen, N.R., Suddduth, K.A., Drummond, S.T., 1999. Soil electrical conductivity as a crop productivity measure for claypan soils. J. Prod. Agric. 12, 607–617.

Kitchen, N.R., Drummond, S.T., Lund, E.D., Sudduth, K.A., Buchleiter, G.W., 2003. Soil electrical conductivity and topography related to yield for three contrasting soil–crop systems. Agron. J. 95, 483–495.

Kitchen, N.R., Snyder, C.J., Frazen, D.W., Wiebold, W.J., 2002. Educational needs of precision agriculture. Precision Agric. 3, 341–351.

Lark, R.M., Stafford, J.V., 1997. Classification as a first step in the interpretation of temporal and spatial variation of crop yield. Ann. Appl. Biol. 130, 111–121.

Lark, R.M., 1998. Forming spatially coherent regions by classification of multivariate data: an example from the analysis of maps of crop yield. Int. J. Geogr. Inform. Sci. 12, 83–98.

Lund, E.D., Christy, C.D., Drummond, P.E., 1999. Practical applications of soil electrical conductivity mapping. In: Stafford, J.V. (Ed.), Precision Agriculture ’99. Proceedings of the Second European Conference on Precision Agriculture. Denmark, 11–15 July 1999. SCI, London, UK, pp. 771–779.

Lund, E.D., Christy, C.D., Drummond, P.E., 2001. Using yield and soil electrical conductivity (EC) maps to derive crop production performance information. In: Robert, P.C., Rust, R.H., Larson, W.E. (Eds.), Proceedings of the Fifth International Conference on Precision Agriculture. Minneapolis, MN, 16–19 July 2000. ASA, CSSA, and SSSA, Madison, WI (CD-ROM computer file).

MacMillan, R.A., Pettapiece, W.W., Watson, L.D., Goddard, T.W., 1998. A landform segmentation model for precision farming. In: Robert, P.C., Rust, R.H., Larson, W.E. (Eds.), Proceedings of the Fourth International Conference on Precision Agriculture. St. Paul, MN, 19–22 July 1998. ASA, CSSA, and SSSA, Madison, WI, pp. 1335–1346.

McBratney, A.B., DeGruijter, J.J., 1992. A continuum approach to soil classification by modified fuzzy *k*-means with extragrades. J. Soil Sci. 43, 159–175.

McNeill, J.D., 1992. Rapid accurate mapping of soil salinity by electromagnetic ground conductivity meters. Advances in Measurement of Soil Physical Properties: Bringing Theory into Practice, Special Publication 30. SSSA, Madison, WI, pp. 209–229.

Odeh, I.O.A., McBratney, A.B., Chittleborough, D.J., 1992. Soil pattern recognition with fuzzy-*c*-means: application to classification and soil–landform interrelationships. Soil Sci. Soc. Am. J. 56, 505–516.

Ping, J.L., Dobermann, A., 2003. Creating spatially contiguous yield classes for site-specific management. Agron. J. 95, 1121–1131.

Rhoades, J.D., Corwin, D.L., Lesch, S.M., 1999. Geospatial measurements of soil electrical conductivity to assess soil salinity and diffuse salt loading from irrigation. In: Corwin, D.L. (Ed.), Assessment of Non-Point Source Pollution in the Vadose Zone. Geophysical Monograph 108. American Geophysical Union, Washington, DC, pp. 197–215.

Sawyer, J.E., 1994. Concepts of variable rate technology with considerations for fertilizer application. J. Prod. Agric. 7, 195–201.

Soil Survey Laboratory Staff, 1992. USDA-SCS National Soil Survey Center, Soil Survey Inventory Report no. 42, version 2.0, August 1992.

Sudduth, K.A., Drummond, S.T., Kitchen, N.R., 2001. Accuracy issues in electromagnetic induction sensing of soil electrical conductivity for precision agriculture. Comput. Electron. Agric. 31, 239–264.

Sudduth, K.A., Drummond, S.T., Birrell, S.J., Kitchen, N.R., 1997. Spatial modeling of crop yield using soil and topographic data. In: Stafford, J.V. (Ed.), Precision Agriculture ’97. Proceedings of the First European Conference on Precision Agriculture, vol. 1. Warwick, UK, 7–10 September 1997. SCI, London, UK, pp. 439–447.

Sudduth, K.A., Kitchen, N.R., Bollero, G.A., Bullock, D.G., Wiebold, W.J., 2003. Comparison of electromagnetic induction and direct sensing of soil electrical conductivity. Agron. J. 95, 472–482.

Sudduth, K.A., Kitchen, N.R., Wiebold, W.J., Batchelor, W.D., Bollero, G.A., Bullock, D.G., Clay, D.E., Palm, H.L., Pierce, F.J., Schuler, R.T., Thelen, K.D. Relating $EC_a$ to soil properties across the north-central USA. Comput. Electron. Agric., this issue.

Thompson, A.L., Gantzer, C.J., Anderson, S.H., 1991. Topsoil depth, fertility, water management, and weather influences on yield. Soil Sci. Soc. Am. J. 55, 1085–1091.

van Alphen, B.J., Stoorvogel, J.J., 1998. A methodology to define management units in support of an integrated, model-based approach to precision agriculture. In: Robert, P.C., Rust, R.H., Larson, W.E. (Eds.), Proceedings of the Fourth International Conference on Precision Agriculture. St. Paul, MN, 19–22 July 1998. ASA, CSSA, and SSSA, Madison, WI, pp. 1267–1278.

Whelan, B.M., McBratney, A.B., 2000. The null hypothesis of precision agriculture management. Precision Agric. 2, 265–279.

Zhang, N., Taylor, R., 2001. Applications of a field-level geographic information system (FIS) in precision agriculture. Appl. Eng. Agric. 17, 885–892.