Accepted for publication 9 September 2003. Published 29 October 2003.

Use of Soil Electroconductivity in a Multistage Soil-Sampling Scheme

Alison B. Tarr, USDA-NASS Agricultural Statistician, 210 Walnut, Suite 833, Des Moines, IA 50309; **Kenneth J. Moore,** Professor, Department of Agronomy, Iowa State University, Ames 50011; **Philip M. Dixon,** Professor, Department of Statistics, Iowa State University, Ames 50011; **C. Lee Burras,** Associate Professor, Department of Agronomy, Iowa State University, Ames 50011; **Mary H. Wiedenhoeft,** Associate Professor, Department of Agronomy, Iowa State University, Ames 50011

Corresponding author: Alison B. Tarr. Alison_Tarr@nass.usda.gov

Tarr, A. B., Moore, K. J., Dixon, P. M., Burras, C. L., and Wiedenhoeft, M. H. 2003. Use of soil electroconductivity in a multistage soil-sampling scheme. Online. Crop Management doi:10.1094/CM-2003-1029-01-RS.

Abstract
The inherent variability of pasturelands makes it difficult to sample soils and accurately characterize a pasture. Indirect methods such as soil electroconductivity (EC) can be used to rapidly, noninvasively, and inexpensively quantify soil variability. The objective of this study was to determine if rapidly collected, georeferenced soil information could be used to propose an accurate, multistage sampling scheme for five soil variables in a central Iowa pasture. Results from this study suggest that the use of noninvasively collected soil EC and topographic data along with fuzzy k-means clustering can be used to delineate relatively homogeneous sampling zones. Consequently, these easily defined sampling zones can beneficially serve as a more directed approach to soil sampling.

Introduction


Fig. 1. Rolling topography of pastures.

Devising a soil-sampling scheme in a pasture situation is difficult due to the inherent variability in pasture landscapes (Fig. 1). The design of traditional sampling schemes, such as grid and triangular, overlook a very important truth in field studies: certain areas of a field are more similar than other areas of the field. This fact is also the fundamental principle of geostatistics: points that are located close together are often more similar than points located far apart. This principle can be applied to generating a sampling scheme for a field situation that is more efficient.

A “good” sampling scheme should be able to quantify field variability as accurately as possible and with as few sampling points as possible. An initial step in sampling a field may be to divide the field into a number of homogeneous strata (5). Stratified sampling requires taking one or multiple samples within each stratum (15). If the areas within the strata were homogeneous, this would support the principle of geostatistics by grouping together points within a field that are similar. Two-stage sampling designs begin with an initial sampling of primary units and then secondary units are selected from each of the selected primary units (15). Further stages of sampling from the secondary or higher-order units may follow and are termed multistage sampling. However, how does one know if areas of a field are similar if samples have not yet been taken?

One way to quickly measure field variability is by use of electromagnetic induction (EMI). Soil electrical conductivity (EC) can be measured on an extremely small grid in a rapid, easy and nondestructive manner by the use of EMI. Soil EC is affected by a number of soil characteristics including soil water content, dissolved salt content, clay content and mineralogy, and soil temperature (11). Soil EC, as measured by EMI, has been correlated with clay content (20), soil water content (8), sand deposition (9), total soluble salts (20), yield (7), and soil available N (6). Benefits from the relationship between soil EC and various soil properties include improved soil mapping, prediction, and management.

In this study, the coupling of soil EC measurements with global positioning systems (GPS) was used to rapidly, easily, and nondestructively collect georeferenced data. By using this information to measure field variability within the pasture, a sampling scheme was devised. Sampling efficiency could be improved by sampling a field more densely in areas that are heterogeneous and less densely in areas that are homogeneous; thus, a stratified sampling scheme was used. The objective of this study was to determine if rapidly collected, georeferenced soil information could be used to propose an accurate, multistage soil-sampling scheme.

Pasture Site Description

Research was conducted at the Iowa State University Rhodes Research Farm (41°52'N, 93°10'W) in central Iowa. The Wisconsin loess-covered landscape has an underlying Yarmouth-Sangamon paleosol. The soils are primarily slope and erosion phases of the Fayette (Fine-silty, mixed, superactive, mesic Typic Hapludalfs) and Clarinda (Fine, smectitic, mesic Vertic Argiaquolls) series (T. E. Fenton, *personal communication*, 2001). The pasture site of the study included topographically distinct summit, sideslope, toeslope, backslope, and opposite summit landscape positions (Fig. 2).

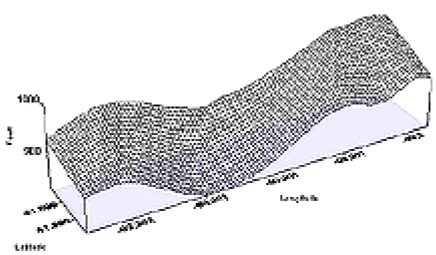

Fig. 2. Wireframe map illustrating topographic variation of pasture site (Golden Software, Inc., Golden, Colorado). Units of feet shown above mean sea level.

Sampling Methods

A dense soil-sampling grid consisting of 116 points was devised for a 1-acre, nongrazed grass-legume pasture (Fig. 3). Sampling points were arranged in a triangular grid with inter- and intra-row separation distances of 19.7 ft. In order to obtain data from samples located closer than 19.7 ft, an additional point was sampled within each row at randomly chosen 3.3 or 6.6 ft separation distances. This short range variation in soil samples was investigated in order to obtain a more reliable experimental semivariogram model (3).

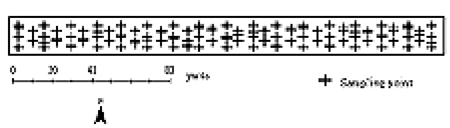

Fig. 3. Initial dense sampling scheme (n = 116).

Soil EC estimates were obtained with a Geonics EM-38 (Geonics, Ontario, Canada) as it was pulled behind a four-wheel drive vehicle in a nonconductive cart. The EM-38 was operated in the vertical dipole orientation at 0.65 ft above the soil surface. The EM-38 integrates over an area approximately equal to its length of 3.3 ft and over a depth of approximately 9.8 ft (12). However, the measurement is primarily influenced by the 0-to-4.9-ft depth increment (12). Given the speed of travel and rate of EC data collection, an EC reading was logged approximately every 13 ft along transects spaced 6 ft apart throughout the pasture. Each soil EC measurement was georeferenced using a Trimble GPS Pathfinder Pro XR receiver (Trimble, Sunnyvale, CA), and all GPS locations were differentially corrected (DGPS) to obtain 3-to-6-ft accuracy. EM-38 measurements were recorded via a direct connection to Trimble System Controller 1 Asset Surveyor software (Trimble, Sunnyvale, CA) in the GPS datalogger. Positional data for the soil EC values were corrected for the lag distance between GPS receiver and the EM-38 instrument. Soil EC values at each of the 116 grid points were interpolated from the dense data set of the 834 georeferenced EC points.

Soil samples were collected via coring following the EM-38 measurements. At each of the 116 sampling sites, five 6-inch soil cores were collected and combined for soil pH and available P and K analysis in the Iowa State University Soils Testing Laboratory (Ames, IA). Organic matter was analyzed from a single core composed of three depth increments to 18 inches, using a dry combustion method. Organic matter percentage averaged across all three depth increments was reported. To quantify soil moisture, a single core composed of seven 6-inch samples was taken. Each 6-inch sample was analyzed using the gravimetric moisture method (2), and average percent soil moisture was reported.

Elevation data were recorded using a Leica System 500 real time kinematic (RTK) system (Leica, Switzerland), and slope data were calculated from this using ArcView 3.2 Spatial Analyst (ESRI, Redlands, CA). Geostatistical analyses were performed using ArcView 8.1 ArcGIS Geostatistical Analyst (ESRI, Redlands, CA).

Multistage Sampling Scheme

Multistage sampling was examined as a stepwise method to create relatively homogeneous sampling zones. Using recorded soil EC and topographic data, a fuzzy k-means algorithm was implemented as the next step in the multistage sampling scheme. The algorithm was used to stratify the field into relatively homogeneous zones based on the densely collected soil EC and topographic data. The fuzzy k-means method has been utilized for classifying soil and landscape data when binary or strictly discrete groupings are not adequate to describe natural systems (4). Given the continuous nature of soils, fuzzy set classification provides a suitable means of classifying areas of a field.

Elevation, slope, and apparent soil EC were used to delineate zones using the software program Management Zone Analyst (18). Based on the software output, five zones appeared optimal for establishing strata of homogeneity in the pasture (Fig. 4). Within these five strata, two intensities of a ranked set sampling scheme (10) were analyzed: n = 30 and n = 15 (Figs. 5 and 6). Ranked set sampling was first described by McIntyre (10) as a method for obtaining more precise and unbiased measurements of forage yield. The five strata delineated by clustering corresponded to the sets in ranked set sampling. The points within each of the five strata were ranked in order of EC value magnitude. Soil EC was chosen as a concomitant variable because it was the variable most easily and accurately collected (14), and it was correlated with the soil variables of interest. When constructing the n = 30 scheme, six points were selected in each of the five strata. With this scheme, the six points were chosen based on maximizing the within-zone variation of soil EC. The six points were selected based on choosing the minimum, maximum, and four in-between quantile values of soil EC within each zone. Maximum within-zone variation was sought in order to maintain the variability identified throughout the field. Similarly, when devising the n = 15 scheme, three points were selected in each of the five strata with the goal of maximizing the within-zone variation of the concomitant variable, soil EC. The three points were selected based on choosing the minimum, maximum, and median values of soil EC within each zone.

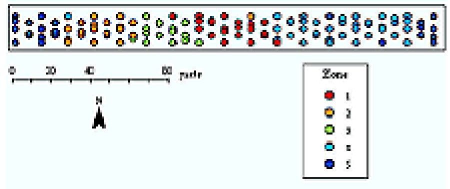

Fig. 4. Fuzzy clustering results for the initial sampling scheme (n = 116).

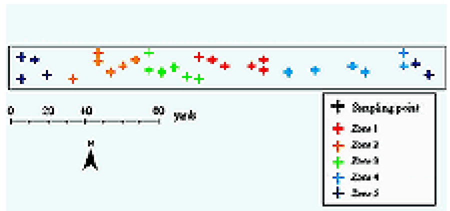

Fig. 5. Sampling points for multistage sampling scheme (n = 30).

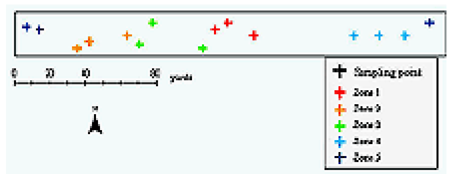

Fig. 6. Sampling points for multistage sampling scheme (n = 15).

Field Characterization

The statistical summaries of topographic and soil attributes for the initial, dense grid (n = 116) sampling scheme indicated a range in elevation of 21 ft (16). Large CVs and ranges for soil P, K, pH, OM, and moisture illustrated the magnitude of soil variability within the pasture (16). The degree to which soil EC can detect this soil variability improves our ability to delineate homogeneous sampling strata.

How well soil EC identifies soil variability depends upon soil EC's relationship with the soil parameters of interest. The results of the large database indicated a strong correlation between soil EC and soil pH, elevation and soil K (r values greater than 0.5). Soil EC was moderately correlated with soil moisture and OM values ($0.10 < r < 0.50$) and weakly correlated with soil P and slope ($r \leq |0.10|$) (16).

These correlations were not of primary interest in our objectives, however. Of interest was determining whether soil EC could be used effectively to identify soil spatial variation and zones of homogeneity from which to sample. In the pasture of study, variability in soil EC appeared closely related to the variation in landscape position and depth to paleosol (T. E. Fenton, *personal communication*, 2002). Higher values of soil EC were measured in the toeslope positions. These positions have a higher moisture content and are underlain by a clay-textured paleosol (Clarinda series). Lower values of soil EC were measured upslope on the summit positions where the soils were developed entirely in loess. Middle values were measured on the backslope where the soils are formed in loess and the underlying paleosol. Because the soil was not dominated by carbonates, the variation in soil EC values was likely related to soil moisture content and textural properties (1). Textural properties influence soil parameters such as organic matter and ionic properties; thus, it was concluded that soil EC is measuring variation in soil properties related to moisture and texture.

Performance of Fuzzy Classification

Using elevation, slope, and apparent soil EC data, a fuzzy k-means clustering algorithm resulted in the delineation of 5 zones throughout the pasture (Fig. 4). This clustering agreed well with landscape position. Zone 1 included bottomland and backslope characteristics; Zone 2 was primarily a sideslope; Zone 3 was primarily bottomland; Zone 4 combined all three landscape positions, but with more gently rolling sideslopes compared to Zone 2; Zone 5 was a region consisting primarily of summit land but with some sideslope area. Cluster membership was spatially discrete with only a few points that were nonadjacent to other members of their zone. Zone 5 included points on both the west and east ends of the pasture, but this separation in zone membership was likely due to the repeating landscape pattern in the field. Zone 5 revealed a repeated summit from the repeating summit, sideslope, toeslope, and backslope pattern in the field. Table 1 quantitatively describes each of the five strata. It is worth noting that the five zones are not of equal size. The fuzzy clustering algorithm reiteratively classified each of the 116 points until each point in a zone was more similar to the cluster centroid than to any other cluster. Therefore, a relatively small amount of variability in soil measurements was expected within each zone. Zone 3 was primarily a bottomland area and it exhibited the most variability in soil P, pH, organic matter, moisture, and EC. Zone 5 showed the most variability in soil K.

Table 1. Mean and standard deviation (SD) for chemical and physical soil attributes shown for each zone.

	Zone 1		**Zone 2**		**Zone 3**		**Zone 4**		**Zone 5**	
	n = 21		n = 20		n = 15		n = 37		n = 23	
	Mean	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**
Elevation (feet)	979.7	3.3	981.0	3.3	974.4	0.7	989.8	1.6	989.2	3.3
Slope (degrees)	5.5	1.0	7.6	0.8	4.0	1.0	5.9	0.7	3.6	0.7
P-Bray (ppm)*	12.6	7.3	12.9	3.3	21.9	12.0	13.4	4.4	15.8	5.6
K-NH_4AcO (ppm)	111.4	30.3	153.1	30.6	100.8	34.7	193.9	49.1	192.3	64.8
pH (1:1 soil/water)	6.4	0.3	5.8	0.1	6.7	0.4	5.7	0.1	5.8	0.1
OM (%)	2.4	1.0	2.1	0.6	3.1	1.2	2.0	0.5	2.0	0.5
Moisture (%)	27.6	1.7	27.1	0.8	31.1	4.6	27.2	0.9	26.7	0.8
Soil EC (mS/m)	52.1	1.8	42.1	1.9	47.6	3.5	42.1	2.0	40.7	1.6

* ppm is parts per million, OM is organic matter, mS/m is milliSiemens per meter.

With the five strata delineated, an analysis of variance using SAS (SAS Institute, Cary, NC) was performed to determine if the strata were indeed different based upon the measured soil variables. If the zones were significantly different from one another based on the soil parameters, then they would be considered acceptable sampling zones. Results from the ANOVAs for soil P, K, pH, OM, and gravimetric moisture are shown in Table 2 based on the entire data set (n = 116). The results indicated that the effect of zone on all the soil parameters was significant. Thus, the resultant zones from the fuzzy clustering algorithm appear to have delineated significantly different zones based on the five soil attributes.

Table 2. One-way ANOVA results for five zones.

Source	df	**P-Bray**		**K-NH4AcO**		**pH**		**OM**		**Moisture**	
		MS	F*	MS	F*	MS	F*	MS	F*	MS	F*
Zone	4	254.34	6.00	42406.78	20.27	3.92	70.17	4.01	7.38	52.22	14.31
Error	111	42.36	--	2091.75	--	0.06	--	0.54	--	3.65	--

df = degrees of freedom, MS = Mean Square, F = *F* ratio
* Significant at the 0.001 probability level.

Performance of Multistage Sampling Scheme

Fuzzy k-means classification techniques can result in a reduction in sampling intensity because homogeneous areas are not oversampled (13). The new stratified sampling scheme derived using a fuzzy k-means algorithm decreased the number of sampling points by 74% (116 to 30) and 87% (116 to 15), respectively. A reduction in the number of sampling points while maintaining accuracy of field characterization was the goal of this sampling scheme. One method for determining whether this goal was met is to compare the variance of the estimated population total to that of a random sample of the same size (15). When comparing the n = 30 stratified sampling scheme with that of a random sample of 30 points, a general trend of increased variances for the random sample was observed for four of the five soil variables (Table 3). Potassium was the single exception for the n = 30 sampling scheme. This difference in variances was not significant ($P = 0.20$), however, and it may be attributed to an inherently high variability (56 to 369 ppm) in soil K for this pasture. The same general trend of increasing variances with random samples was also evident in the n = 15 sampling scheme. The single exception was soil P, and again, this difference occurred with a relatively variable soil property, and it was not significant ($P = 0.20$). Although few of the stratified-random comparisons were significantly different from one another ($P = 0.20$), the difference in population variances may transfer to a measurable difference in actual field characterization. This effect was not examined. However, reducing the estimation of the population variance improves the precision associated with the sample values.

Table 3. Comparison of estimated population variances between the stratified (strat.) and random (rand.) sampling schemes at two sampling densities (n = 30 and n = 15).

	Estimated population total variances							
	n = 30				n = 15			
	strat.	**rand.**	***F* ratio**	***P* > *F***	**strat.**	**rand.**	***F* ratio**	***P* > *F***
Phosphorus	8803	11554	1.31	0.232	18244	16518	0.91	0.571
Potassium	909319	870687	0.96	0.544	2459667	2667591	1.08	0.442
pH	14	54	3.86	<0.001	48	102	2.13	0.077
OM	99	144	1.45	0.157	250	267	1.07	0.449
Moisture	1586	2460	1.55	0.118	924	1071	1.16	0.389

It is worthwhile to note that the stratified sampling scheme significantly reduced population variance the most for soil pH in both the n = 30 and n = 15 sampling schemes ($P = 0.10$) (Table 3). It is hypothesized that this is because pH is the soil variable most closely correlated with the three noninvasively measured soil parameters used for fuzzy classification. Consequently, as would be expected, stratification worked best for soil variables most closely related to the variable(s) used for fuzzy classification.

Validation of the two new sampling schemes was conducted by interpolating the data from the new sampling schemes to estimate unsampled points in the pasture. Data were interpolated by kriging (3). The predictions resulting from kriging were compared to the actual values at unsampled points known from the original (n = 116) sampling scheme (Fig. 3). Similar to most soil sampling situations, we assumed that we did not know the semivariogram model for the soil variables measured. Therefore, when attempting to find the best semivariogram model, the model with the lowest root mean square error (RMSE) of prediction for cross-validation of the sampled points was chosen (17). The RMSE was a measure reporting the precision of prediction. It should be as small as possible for unbiased and precise predictions (17). For cross-validation, each sampling point from a sampling scheme was removed in turn and kriging was used to predict its value based on the remaining points. The ArcGIS extension Geostatistical Analyst was used for these procedures (ESRI, Redlands, CA).

The 86 and 101 points not included in the n = 30 and n = 15 sampling schemes, respectively, were used as validation sets. These large validation sets were compared with the predicted soil values from kriging (Table 4). A comparison of predicted versus actual values for the soil parameters described how well the kriged results from each sampling scheme estimated unsampled points. Soil pH at unsampled points was predicted the best out of the five soil variables (Table 4). This result could again be attributed to the fact that pH is a soil variable most closely correlated with the three noninvasively measured soil parameters used for fuzzy classification. The results of soil pH indicated that the higher sampling density resulted in a nearly twofold decrease in prediction error, and it also improved the r^2 value (Table 4). The increase in prediction error associated with the decrease in sampling intensity may or may not be of consequence depending on the cost-to-benefit ratio of additional sampling. In the case of soil pH, the additional cost and effort required to sample the 15 additional points would have to be weighed against the potential benefits from more precise application of lime.

Table 4. Validation set root mean square errors (RMSE) of soil data prediction for kriging the n = 30 and n = 15 sampling schemes. Coefficient of determination (r^2) between predicted and actual values for validation set.

	n = 30		n = 15	
	RMSE (unit)	**r^2**	**RMSE (unit)**	**r^2**
P-Bray, ppm*	4.903	0.549	6.884	0.265
K-NH_4AcO, ppm	45.70	0.518	44.160	0.458
pH, 1:1 soil/water	0.169	0.858	0.306	0.555
OM, %	0.762	0.187	0.733	0.250
Moisture, %	1.611	0.501	2.414	0.044

* ppm is parts per million, OM is organic matter.

The results of soil phosphorus and moisture were similar to soil pH (Table 4). There was an increase in prediction error for the unsampled points when fewer samples were measured, and the coefficient of determination was significantly smaller for the lower density sampling scheme. Soil moisture exhibited an especially poor r^2 value for the n = 15 sampling scheme. Several hypotheses may account for this result. First, this result may be due to the fact that soil moisture gradients did not correlate well with the zones produced by fuzzy classification of the three noninvasively measured soil parameters. Second, the selection of points within each zone may not have been ideal for accurate detection of pasture variability in moisture. Third, the reliability of the experimental semivariogram is affected by the size of the sample and the configuration of the sample (19). With only 15 sampling points and an irregular sampling pattern, the resultant experimental semivariogram may not have provided an accurate model of soil variability. In fact, Webster and Oliver (19) state that experimental variograms based on fewer than 50 data often have little or no evident structure. However, as the size of the sample is increased, the structure of the variogram becomes clearer (19). In the field, however, the size of the sample is often determined by the availability of resources such as time, labor, and money.

Soil potassium and organic matter displayed different results than pH, phosphorus, and moisture. With both potassium and organic matter, the RMSE of prediction decreased when fewer points were sampled (Table 4). However, this decrease in RMSE was not substantial. The r^2 value for potassium decreased when fewer points were sampled (similar to pH, phosphorus and moisture). The r^2 value for organic matter actually increased for the n = 15 sampling scheme. This aberrant outcome was likely a rare result.

Conclusions

Soil EC can be used to detect soil variability in pastures. Using EMI techniques, such data collection is rapid, easy, and noninvasive. When soil EC data was coupled with georeferenced topographic information such as elevation and slope, a large database was available to describe field variability. This large database was incorporated with fuzzy clustering as a way to delineate homogeneous sampling zones in the pasture. Thus, the zones provided an effective starting point for soil sampling. As a final stage in the multistage sampling scheme, ranked set sampling insured an unbiased selection of points (10) while maintaining within cluster variability.

The study suggests that soil variables most closely related to those used for clustering are predicted with the least error at unsampled points. Soil pH was most highly correlated with soil EC, and the prediction accuracy of pH at unsampled points was highest (Table 4). In general, there was a loss in prediction accuracy resulting from a decrease in sampling intensity. However, this loss in predictive accuracy may not have economic or management consequence to the producer.

Stratification was useful in dividing a heterogeneous population such as a pasture into relatively homogeneous subpopulations, or sampling zones. Because the pasture of study included five topographically distinct landscape positions often inherent to pastures larger in scale, the sampling method explored in this study may be applicable to larger pastures. By stratification of this pasture using the fuzzy k-means clustering algorithm, a more directed approach to soil sampling was taken. A more optimal sampling scheme covers the same area with fewer sampling points, less time, and less labor while using rapid, noninvasive, geospatial tools. Knowing about field variation without an invasive and time-consuming survey may save labor and can direct efforts for sampling.

Literature Cited

1. Brevik, E. C., and Fenton, T. E. 2002. Influence of soil water content, clay, temperature, and carbonate minerals on electrical conductivity readings taken with an EM-38. Soil Surv. Horiz. 43:9-13.
2. Buckman, H. O., and Brady, N. C. 1971. The Nature and Properties of Soils. 7th ed. Macmillan, New York.
3. Burgess, T. M., and Webster, R. 1980. Optimal interpolation and isarithmic mapping of soil properties. I. The semi-variogram and punctual kriging. J. Soil Sci. 31:315-331.
4. Burrough, P. A. 1989. Fuzzy mathematical methods for soil survey and land evaluation. J. Soil Sci. 40:477-492.
5. Cline, M. G. 1944. Principles of soil sampling. Soil Sci. 58:275-288.
6. Eigenberg, R. A., Doran, J. W., Nienaber, J. A., Ferguson, R. B., and Woodbury, B. L. 2002. Electrical conductivity monitoring of soil condition and available N with animal manure and a cover crop. Agric. Ecosyst. Environ. 88:183-193.
7. Jaynes, D. B., Colvin, T. S., and Ambuel, J. 1995. Yield mapping by electromagnetic induction. In: Site -Specific Management for Agricultural Systems. ASA-CSSA-SSSA, Madison, WI.
8. Kachanoski, R. G., Gregorich, E. G., and Van Wesenbeeck, I. J. 1988. Estimating spatial variations of soil water content using noncontacting electromagnetic inductive methods. Can. J. Soil Sci. 68:715-722.
9. Kitchen, N. R., Sudduth, K. A., and Drummond, S. T. 1996. Mapping of sand deposition from 1993 midwest floods with electromagnetic induction measurements. J. Soil Water Conserv. 51:336-340.
10. McIntyre, G. A. 1952. A method for unbiased selective sampling, using ranked sets. Aust J. Agric. Res. 3:385-390.
11. McNeill, J. D. 1980. Electrical conductivity of soils and rocks. Technical Note TN-5. Geonics, Ltd., Mississauga, Ontario, Canada.
12. McNeill, J. D. 1980. Electrical conductivity of soils and rocks. Technical Note TN-6. Geonics, Ltd., Mississauga, Ontario, Canada.
13. Odeh, I. O. A., McBratney, A. B., and Chittleborough, D. J. 1990. Design of optimal sample spacings for mapping soil using fuzzy-k-means and regionalized variable theory. Geoderma 47:93-122.
14. Patil, G. P., Sinha, A. K., and Taillie, C. 1994. Ranked set sampling. Pages 167-200 in: Environmental Statistics, Handbook of Statistics, Vol. 12. G. P. Patil and C. R. Rao, eds. Elsevier Science, Amsterdam.
15. Sampford, M. R. 1962. An Introduction to Sampling Theory with Applications to Agriculture. First ed. Oliver and Boyd, Edinburgh.

16. Tarr, A. B. 2002. Geostatistical use of indirect methods for improving sampling accuracy in pastures. M.S. thesis, Iowa State University, Ames.
17. Triantafilis, J., Odeh, I. O. A., and McBratney, A. B. 2001. Five geostatistical models to predict soil salinity from electromagnetic induction data across irrigated cotton. Soil Sci. Soc. Am. J. 65:869-878.
18. University of Missouri-Columbia and USDA-ARS. 2000. Management Zone Analyst software. Release 1.0. Online. USDA-ARS, Columbia, MO. Accessed Sept. 27, 2001.
19. Webster, R., and Oliver, M. A. 2001. Geostatistics for Environmental Scientists. John Wiley & Sons, Ltd., Chichester.
20. Williams, B. G., and Hoey, D. 1987. The use of electromagnetic induction to detect the spatial variability of the salt and clay contents of soils. Aust. J. Soil Res. 25:21-27.