SOIL MOISTURE, ORGANIC MATTER AND POTASSIUM INFLUENCES ON EC_A MEASUREMENT

R. R. Struthers
Agronomy Department
Purdue University
West Lafayette, Indiana

C. J. Johannsen
Agronomy Department
Purdue University
West Lafayette, Indiana

D. K. Morris
Biological and Agricultural Engineering Department
Louisiana State University AgCenter
Baton Rouge, Louisiana

ABSTRACT

Spatial variability of soil physical and chemical properties is a fundamental element of site-specific soil and crop management. Since its early implementation in agriculture as a method of measuring soil salinity, the acceptance of Apparent Electrical Conductivity (EC_a) in agriculture has been popular as a method of determining the spatial variability of soil physical and chemical properties that influence the EC_a estimates. It was the objective of this study to examine the spatial-temporal stability of EC_a estimates in selected Eastern Corn Belt soils. By employing spatial statistics to the EC_a estimates, this study was able to determine that on a field scale, EC_a estimates at 0-30 and 0-90cm depths were variable at distances that ranged from 25 to 115m. Only one soil mapping unit tested significant at 0-30 cm while there were no significant results between individual soil mapping units and EC_a at 0-90 cm over the five years data that were collected. EC_a estimates were also collected in west-central Indiana on small plots (6x42 m) of prairie and forested soils on a weekly basis over a period of 12 -13 weeks to assess spatial-temporal EC_a estimates at 0-30 cm depth. Spatial autocorrelation distance for the EC_a at 0-30cm depths for the six sub-fields varied from 2 to 10m. Some weeks were significant for soil moisture, organic matter or K but the results were not consistent using either the ordinary least squares (OLS) or spatial process models, and the causality relationship could not be established as they were not consistent. This study concludes that apparent electrical conductivity (EC_a) does not provide consistent results for the measurement and/or assessment of soil moisture content, organic matter and potassium.

Keywords: Apparent Electrical Conductivity, spatial variability, spatial autocorrelations, soil moisture, organic matter, potassium.

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INTRODUCTION

Precision agriculture uses technology to manage soils and crops in a site-specific manner. Precision agriculture began more than 20 years ago in the early to mid-eighties. Wiebold et al (1998) stated that along with yield mapping, some producers have shown an interest in characterizing the variability of soil. However, one must be aware that there is no single measurement that helps explain the effect that soil variability has on corn yield (Kitchen et al., 2003).

The objectives of this study were to (1) verify the spatial and temporal stability of apparent electrical conductivity (EC_a) at 0-30 and 0-90 cm depths in selected Eastern Corn Belt soils and (2) assess the correlation of organic matter, potassium (K) and soil moisture (%v/v) to EC_a.

LITERATURE REVIEW

Corwin and Lesch (2005) stated the first application of apparent electrical conductivity (EC_a) in agriculture was for the measurement of soil salinity. Research in this area was primarily conducted by Rhoades and his colleagues in the 1970's at the USDA-ARS Salinity Laboratory in Riverside, CA. Soil salinity is determined by the quantity of mineral salts found within a soil at different depths (Corwin and Lesch, 2005).

The electrical conductivity of a soil is a measurement of how an electrical current is transmitted through the soil (Corwin and Lesch, 2003). Apparent electrical conductivity is affected by soil temperature, physical and chemical properties of the soil including the concentration of minerals of the soil water, soil structure, and clay content (Geonics Limited, 1980). Relationships between EC_a and soil moisture, salinity and soil properties were tested by Corwin and Lesch (2003) demonstrating three soil electrical conductivity pathways. Resh (1991) reported that "for every 1°C temperature change, the conductivity of a nutrient solution will increase by around 2%". More simply, he noted that small changes in temperature make a large difference in electrical conductivity.

Soil EC_a estimates have been used for quantifying and monitoring soil salinity in irrigated agricultural areas of arid soils (Spies and Woodgate, 2005). Other uses of EC_a reported in precision agriculture include the improvement of the soil mapping units, the design of management zones (Sudduth et al., 2003) and soil drainage patterns classification (Kravchenko et al., 2002).

Apparent electrical conductivity has been used to characterize field variability in precision agriculture because of the ease in which large amounts of geo-referenced data can be collected (Corwin and Lesch, 2003). The relationship between EC_a and crop yield has been reported to be significant within crop treatments and fields but has been inconsistent across years (Jaynes et al., 1993; Sudduth et al., 1995; Kitchen et al., 1999). Lund et al. (1999) and Sudduth et al. (2001) state "it is important to note that while the magnitude of measured EC_a fluctuates over time, the spatial patterns of EC_a remain constant". Kitchen et al. (1999) stated that climate, crop type and specific field information are usually required to understand the relationships for any given site year. Kachanoski et al. (1988) found a linear relationship between EC_a and soil moisture up to 25% volumetric water content, above which they found little change in soil EC_a. Heiniger et al. (2003) also found that in general, that the direct relationships between EC_a and P, K, Ca, Mg, Mn, Zn, and Cu on nine fields studied in 1999 were either weak or non-significant. Brevik et al. (2006) reported soil moisture variations affected EC_a estimates at different landscape positions. They also stated if EC_a is to be used in precision agriculture, measurements should be collected when soils are moist. Corwin and Lesch (2005) state similar results were found for the relationship between EC_a and soil salinity.

The cost of intensively soil sampling a field is often greater than the savings from the reduction in fertilizer or lime (Swinton and Mubariq, 1996; English et al., 1999). Heiniger et al. (2003) stated that it seems logical to believe EC_a could be used to measure the nutrient content of the soil but concluded that there was generally a weak relationship between EC_a and soil test results for P, K, Ca, Mg, Mn, Zn, and Cu. Omonode and Vyn (2006) also concluded that there is a weak correlation between EC_a and organic matter, P and K.

Spatial dependence and spatial heterogeneity are known as the main problems in statistical analysis (Smithwick et al., 2005). Spatial dependence can be caused by many measurement problems in applied research. Two examples of these are the arbitrary definition of spatial units by artificial boundaries and the problems of spatial aggregation due to these arbitrary lines (Openshaw, 1984). Rather than use arbitrary boundaries for analysis, (Jelinski and Wu, 1996) suggest one possible solution is to utilize natural entities. Fotheringham and Rogerson (1993) stated it is known that applying statistical results from a large to a small scale will result in serious errors. Rather than risk statistical and analytical errors by arbitrarily defining boundaries, Anselin and Getis (1992) suggest determining spatial autocorrelation or the distance at which a variable is related to one another.

MATERIALS AND METHODS

Description of Study Sites

The first portion of this study was conducted on 4 sub-fields totaling approximately 46 ha on Purdue University's Davis Purdue Agriculture Center (DPAC) in Randolph County, Indiana, USA (40°14'38" N 85°8'55" W) on soils formed on Wisconsin age glacial till. The field is non-irrigated with most significant topographic relief located in the northwest, west central and southeast corner of the field. The Order 2 Soil Survey was digitized and cartographic errors removed based on a 0.1 m contours derived from a topographic map collected in 2004. Major soil mapping units for an Order 2 Soil Survey are Blount (fine, illitic, mesic Aeric Epiaqualfs), Glynwood (fine, illitic, mesic Aquic Hapludalfs), Morley (fine, illitic, mesic Oxyaquic Hapludalfs), Pewamo (fine, mixed, active, mesic Typic Argiaquolls), and Saranac (fine, mixed, active, mesic Fluvaquentic Endoaquolls). The geomorphology of the soil series are: Blount, Glynwood and Morley – till plain moraine, Pewamo – depression on till plain and Saranac – flood plain (Neely, 1987).

The second portion of this study was conducted on 3 plots of forest-derived soils and 3 plots of prairie-derived soils on Purdue University's Agronomy Center for Research and Education (ACRE) in Tippecanoe County, Indiana, USA (40°28'45" N 86°59'36" W) on soils formed on Wisconsin age glacial till with each plot measuring 6 x 42 m. The forest soils consisted of Rockfield (fine-silty, mixed, superactive, mesic Oxyaquic Hapludalfs) and Toronto (fine-silty, mixed, superactive, mesic Udollic Epiaqualfs). The prairie soils contain Drummer (fine-silty, mixed, superactive, mesic Typic Endoaquolls) and Raub (fine-silty, mixed, superactive, mesic Aquic Argiudolls). The geomorphology of the soil series are: Drummer – depressions on till plain, Raub, Rockfield and Toronto – till plain moraine (Ziegler, 1998).

Data Collection

At the DPAC study site, EC_a estimates were collected within each sub-field using a Veris 3100® sensor cart (Veris Technologies, Salina, KS) that operates on a principle of electrical resistivity. Prior to each data collection, the signal output and electrical continuity of the Veris 3100 were checked per the manufacturer's instructions and specifications to ensure proper functioning of the tool.

The measurements were taken on average spatial distance of 3 m between points in the direction of travel, with transects of ≤ 10m on 28 May 1999, 2 June 2000, 6 November 2001, 15 October 2002 and 23 October 2003 following a previous crop of soybean [*Glycine max* (L) Merr]. Transects were also created in ArcGIS 8.3 (ESRI, 2003) at a distance of 18m and then buffered to a width of 2.5m. Any points that fell within this buffer zone were selected and used for analysis. The same transects and buffer zones were used for each subsequent EC_a dataset to ensure that analyses were conducted using EC_a points that fell on the same transect and the 2.5m buffer. Two sets of EC_a estimates were collected at depths of 0-30cm and 0-90cm as described by Veris Technologies (2006). EC_a estimates were georeferenced using a differential global positioning system (DGPS) with an accuracy of ± 1 m.

The Order 2 Soil Survey (Neely, 1987) was digitized and overlain with the EC_a data. A soil delineation line of 0.5mm at a scale of 1:15,840 can be interpreted to an actual ground distance of 8m. In addition to the 8 m soil line, the buffer was exaggerated by 7.4m both inside and outside of this line producing an approximate 23m-transition zone. The exact width of the transition line at any specific location depends on the gradation of one soil to another. This distance is actually based on field topography and the distance mechanical applicators require when changing application rates. Each soil mapping unit was buffered to a distance of ≈ 11m inside the polygon to capture accurate EC_a estimates and to lessen the influence of transitional soils. EC_a estimates were then extracted for each individual soil mapping unit.

At the ACRE study site, georeferenced EC_a estimates with accuracy of ± 1m were collected using the same Veris 3100 sensor cart as used at the DPAC site. Data were collected on a weekly basis on bare soil at an average distance of 1.5m with transects of 2.5m on 6 x 42m plots beginning 19 July 2004 and ending 22 October 2004. On the same day, 100 evenly spaced soil moisture (%, v/v) data points were collected in the center of the Veris cart path in the direction of travel using a Spectrum TDR 300 ® (time domain reflectometry) soil moisture probe (Spectrum Technologies, East - Plainfield, Illinois) to a depth of 20cm. Soil temperature was measured at a depth of 10cm on bare soil as were daily rainfall amounts by an automated weather station located at ACRE. The plots were tilled to a depth of ≈15 cm following the collection of soil moisture on August 2, August 23, and September 16 to remove any weeds that were present and to remove compacted tire track areas so as not to interfere with the subsequent EC_a estimates. Upon completion of the study, each sub-field was equally divided into 6 sub-plots and soil samples collected and sent to Iowa State University's soil testing laboratory for % OM, P Bray-1, and Mehlich-3 extraction for Ca, Mg, and K measurements.

Statistical Analysis

Often, precision agriculture researchers take point data and interpolate it using equal area grids. Grid size is often arbitrarily determined by the researcher. This study considered the implications of arbitrary grid size determination by interpolating sub-field M1 EC_a point data at 0-90 cm depth for four years into 14 and 45m equal area grids in ArcView 3.3 (ESRI, 2002). The point data were interpolated using inverse distance weighting (IDW) with a power of 2 and 12 nearest neighbors. Once the interpolation was complete, a 1-standard deviation classification scheme was implemented with 1 significant digit.

Maps created with the 14m grid size were reasonably stable for EC_a at 0-90 cm depth over the 4 years. The minimum EC_a estimates varied by only 2 milliSiemens per meter (mS/M). The maximum EC_a estimates varied by 19 mS/M and the means by 12 mS/M. The standard deviations ranged from 7.5 in 2000 to 5.4 in 2001.

Maps created alternatively with a 45 m grid size were more variable over the 4 years. The minimum EC_a estimates for each year varied by 3 mS/M, similar to the 14 m grid size. The maximum EC_a estimates varied by 30 mS/M, or 11 mS/M larger than the 14 m grid size. The mean EC_a estimates varied by 12 mS/M, identical to the 14 m grid size. The standard deviations ranged from 8.9 in 2000 to 5.3 in 2001. In 2000, the standard deviation for each grid size was the largest but the 45m grid size was 1.4 standard deviations larger than the 14 m grid size. The standard deviations for the remaining years were similar.

The difference in the resulting maps between the 14 and 45m grid size caused us to reconsider the use of interpolating point data into arbitrarily sized grids. Jelinski and Wu (1996) stated that such differences are due to the modifiable areal unit problem (MAUP). The modifiable areal unit problem is made up of two elements, scale and aggregation. Openshaw (1984) stated that the scale component occurs when the same data are aggregated into larger units. The aggregation component occurs when the results are influenced by the manner in which the units are arranged. As a result of the suspected MAUP with these data, the analysis for EC_a at 0-30 and 0-90cm depths and the relationship between EC_a and soil chemical properties were done using spatial statistics.

Spatial autocorrelation (SAC) was one of the analyses used to determine the primary relationships of EC_a to soil properties in this study. Moran's I statistic (Anselin, 1992) was used to calculate the coefficient at selected lag distances.

Moran’s I is a measure of autocorrelation similar in interpretation to the Pearson’s correlation statistics. Both statistics have a reported range from + 1.0 demonstrating a strong positive correlation to 0 indicating a random pattern to -1.0 meaning a strong negative spatial autocorrelation. The statistic for Moran’s I is (Anselin, 1992):

$$I = (N / S_0)\sum_i \sum_j w_{ij}(x_i - \mu)(x_j - \mu) / \sum_i (x_i - \mu)^2 \qquad \text{Eq. [1]}$$

where μ is the mean of the variable x and w_{ij} are the components of the spatial weight matrix and S_0 is a factor equal to the sum of the components in the weigh matrix.

Anselin (1995) suggested a method to detect the local patterns of spatial association (LISA) with adjustment for local instabilities in overall spatial association. It can capture the local level of spatial autocorrelation in order to identify areas where values of the variable are both extreme and geographically homogeneous. This enables one to identify so called hot spot areas where the variables are apparent across localities. The local Moran statistic for each observation i may be defined (Anselin, 1995) as follows:

$$I_i = Z_i \sum_{j, j \neq i}^{n} w_{ij} Z_j \qquad \text{Eq. [2]}$$

where the observations Zi and Zj are in standardized form. The weight w_{ij} is in row-standardized form. A pseudo-significance level of the I_i can be found by using a permutation approach. A small p-value such as $P < 0.05$ indicates that location i is associated with the relatively high values of the surrounding locations. A large p-value such as $P > 0.05$ indicates that location i is associated with relatively low values of the surrounding locations.

One can determine the maximum positive spatial autocorrelation distance using the 95% confidence limit for Moran’s I. This value is based on its Z-transformation and examines the significance of the values ($P < 0.05$) with distance. The 95% confidence limits for these transformed values are -1.96 to +1.96 (Doak and Pollock, 2005). That is to say any Z-transformed autocorrelation value that is near the outside range of these two lines is significant, while those closer to zero are not significant. The Z scores are a special application of the transformation rules. The Z score for an item indicates how far and in what direction that item deviates from its distribution's mean and is stated in its standard deviation. The mathematics of the Z score transformations is that if every item in a distribution is converted to its Z score, the transformed scores will have a mean of zero and a standard deviation of one.

For each class, one then quantifies the correlation between the pairs of points. The extent to which the spatial autocorrelation changes with increasing distance classes tells us how far apart measurements must be to be independent of one another, as well as the strength and the sign (either positive or negative) and correlations at each distance. For most precision agriculture applications the strength of SAC will be strongest at very short distances, and then trend downward with increasing distance. In this study, it was not uncommon to see significant SAC reappear at medium to large distances. This is due to the interaction of the area where variables such as EC_a are sampled (Doak and Pollok, 2005).

The result of spatial dependence and heterogeneity is that the observations contain less information than if there had been independence (Anselin, 1992). This author also states that using classical statistics, the properties for the estimators and hypothesis tests will not be maintained when spatial errors are present. When there is spatial dependence and spatial heterogeneity in the spatial models, the ordinary least squares (OLS) estimators will be biased as well as inconsistent (Greene, 1981).

The determination of spatial heterogeneity and dependence requires the spatial weight matrix *w*. Each weight element *wij* in *w* corresponds to a pair of observations at locations *i* and *j*. The GeoDA statistical software package (Anselin, 2005b) was used to test for spatial dependence by means of ordinary least squares (OLS) using a distance matrix. Determination between an OLS, spatial lag or spatial error model was made by examining the Moran's I statistic, z-value and probability. If the Moran's I statistic, z-value and p-value are significant, then spatial autocorrelation is present (Anselin, 1992). The process of determining spatial dependency and heterogeneity are discussed by Anselin (2005a). Five Lagrange Multiplier (LM) test statistics are reported by Anselin, (2005a) and Pryce (2002).

The individual mapping units are labeled alphabetically beginning with A for each soil series found in the whole field. Diagnostics for spatial dependency indicated there was no spatial dependency. Therefore, an ordinary least squares regression becomes the appropriate model for testing whether there is a relationship between EC_a and other variables.

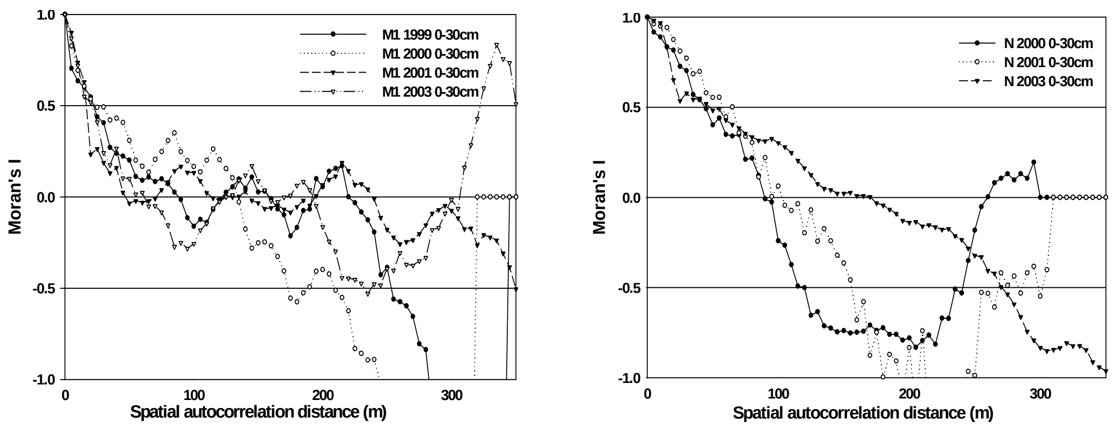
RESULTS AND DISCUSSION

Comparison of EC_a Spatial Autocorrelation Distance

The five soils were represented by the following areas with the 4 test fields at the DPAC study site: Blount (33%), Pewamo (37%), Glynwood (23%), Morley (6%) and Saranac (1%). Visual assessments of surface soil moisture conditions at DPAC the day EC_a estimates were collected for each year were 1999 (dry), 2000 (very wet), 2001 (moist, but not muddy), 2002 (moist but not muddy) and 2003 (wet areas, moist to muddy).

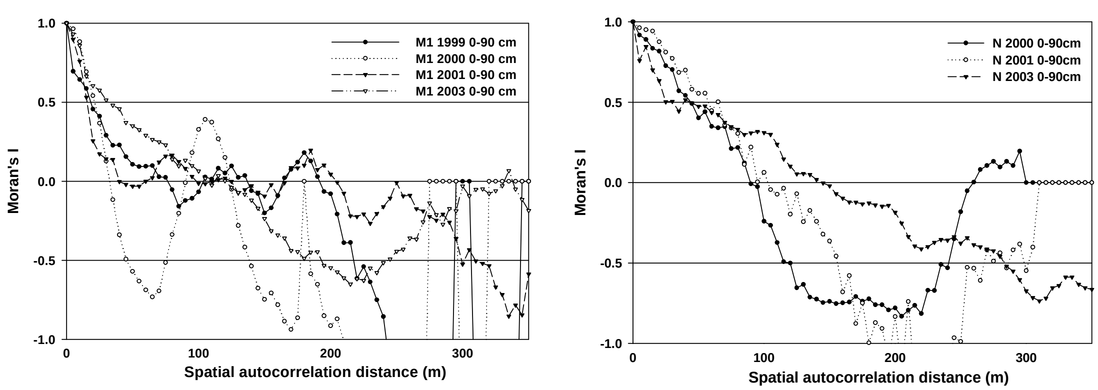
Figure 1 shows the distances at which spatial autocorrelation remains significant and exhibits variable patterns with a maximum positive spatial autocorrelation distance that varies year to year for the EC_a estimates taken at 0-30cm for Fields M1 and P which were representative of the results. The autocorrelation at zero SAC is 1 indicating perfect autocorrelation and begins to decay as SAC distance increases between EC_a estimates to insignificant levels ($P > 0.05$). The most common pattern is to see relatively strong, positive autocorrelation at the smallest distance with either a slow or rapid decline in correlation as the distance increases. The distance at which Moran's I is considered to be significant is dependent on the year that EC_a was collected. This poses a problem if one is to use EC_a estimates to predict corn yield. Note if the distance of spatial autocorrelation of EC_a is 100m, this is saying that at this distance, there is no significant difference in EC_a measured soil properties. For this study site, it was determined the distance of spatial autocorrelation is not the same for subsequent years and that at a 95% confidence limit for EC_a at 0-30cm with a transect of ≤ 10m, the distance of spatial autocorrelation for all the sub-fields ranged from 30 to 110m, the Moran's I ranged from 0.04 to 0.15, the Z values ranged from 2.10 to 5.50 and the P values were significant for all measurements at the 0.05 probability level.

Figure 2 shows the spatial autocorrelation distance for transects ≤ 10 m at a depth of 0-90cm for sub-fields M1 and N, which is a similar pattern to that of 0-30cm. Spatial autocorrelation distance for sub-field M1 ranged from 30 to 90 m. Sub-field P is so similar that one could conclude that the 0-30cm depth might be influencing the measurements. The distance of spatial autocorrelation for all the sub-fields ranged from 25-115m, the Moran's I ranged from 0.05-0.16, the Z vales ranged from 2.07-7.92 and the P values were significant for all measurements at the 0.05 probability level.



a. EC_a @ 0-30 cm depth for sub-field M1 b. ECa @ 0-30 cm depth for sub-field P

Figure 1. Spatial autocorrelation distances for EC_a at a depth of 0-30 cm on ≤10 m transects for (a) sub-field M1 and (b) sub-field P.



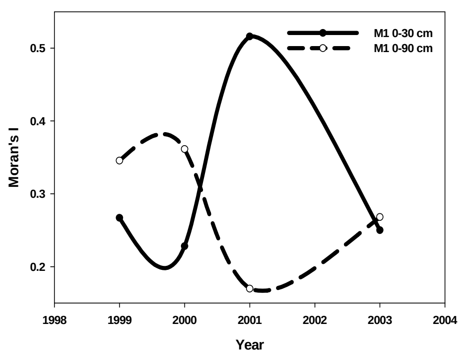
a. EC_a @ 0-90 cm for sub-field M1 b. EC_a @ 0-90 cm depth for sub-field N

Figure 2. Spatial autocorrelation distances for EC_a at a depth of 0-90 cm on ≤ 10 m transects for (a) sub-field M1 and (b) sub-field N.

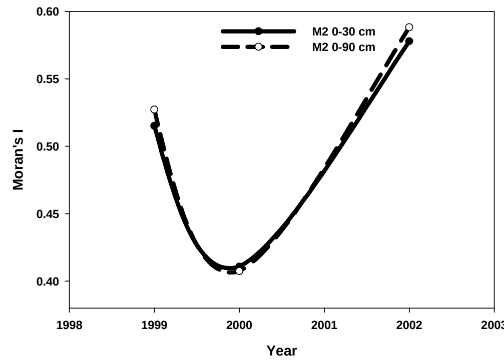
It was difficult to draw any conclusions on which transect width (≤ 10 or 18 m) was meaningful given the variability in SAC distances. The EC_a sensor manufacturer suggests that 12 to 18 m transects will provide a map that adequately identifies the spatial patterns of a field (Veris Technologies, 2006). Lund et al. (1999) and Sudduth et al. (2001) stated that while the variability of measured EC_a values differ over time, the spatial patterns or zones of EC_a remained constant. If the spatial patterns or zones were constant, the SAC distance and slope of the line would be similar each year that data were collected. This research shows that the spatial patterns are quite variable from year to year in each of the four sub-fields that were tested. As a result, it would be difficult to develop management zones using EC_a estimates because the size of the management zones would vary within a field depending on the year that the data were collected.

Spatial Autocorrelation Time Series

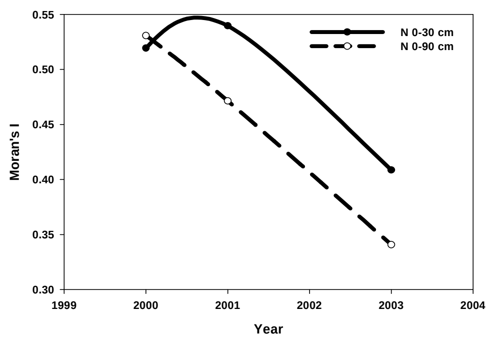
Once the SAC distance was determined for each sub-field and year that EC_a was collected, the 95% confidence limit for SAC distance was used to create a distance matrix to establish the local Moran's I value. Moran's I statistical significance was tested using 10,000 Monte Carlo permutations for each sub-field (Figure 3).



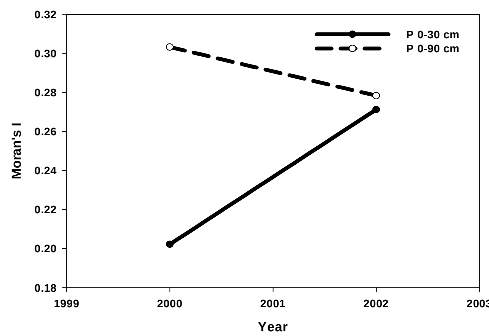
a. Sub-field M1 SAC time series.



b. Sub-field M2 SAC time series.



c. Sub-field N SAC time series.



d. Sub-field P SAC time series.

Figure 3. Spatial autocorrelation (SAC) time series of a) sub-field M1, b) sub-field M2, c) sub-field N and d) sub-field P showing changes with EC_a 0-30 and 0-90 cm with EC_a data collected from 1999-2003.

The results of the EC_a time series analyses at DPAC are curious. One would think that at the 0-90 cm depth, soil moisture conditions would be somewhat stable and less variable. Brevik et al. (2006) stated that there may be a relationship between EC_a and soil moisture if it is assumed that changes in soil moisture follows the pattern of rainfall. However, Das and Mohanty (2005) stated "the saturated hydraulic conductivity, which is highly variable in space, is a primary factor affecting infiltration". Because of the variability in the soil physical and chemical properties across the landscape, it is difficult to conclude how much soil moisture influenced the variability in EC_a estimates.

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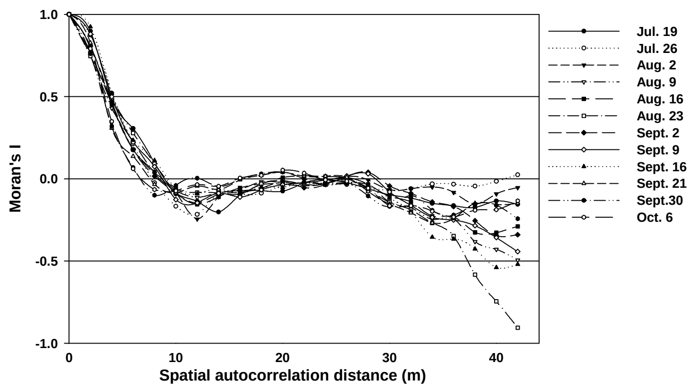
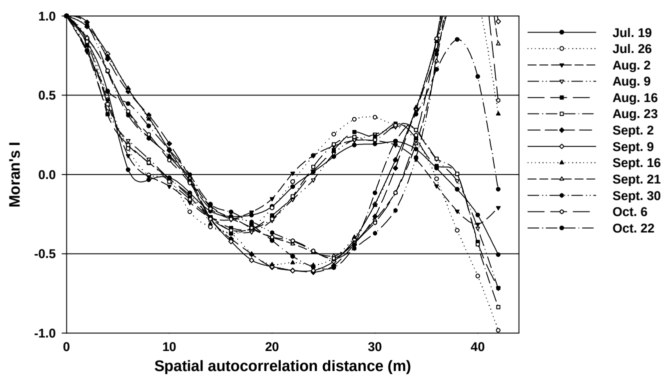
Spatial Autocorrelation Distance

The SAC distance for EC_a on the six plots with four soil series up to thirteen weeks appeared to be stable at a maximum distance of 10 m. Figure 4 shows the representative SAC distances for shallow EC_a of sub-field 131-1 and subfield 31-3 for the twelve weeks that EC_a estimates were collected. The SAC distances for EC_a at 0-90 cm depth are not reported since the correlations with soil moisture, OM and K data were obtained at the 0-30 depth.



a. Field 131-1 EC_a @ 0-30 cm



a. Field 31-3 EC_a 0-30 cm.

Figure 4. Spatial autocorrelation distance for EC_a @ 0-30 cm for 12 weeks for sub-field a) prairie soils in 131-1 and b) forested soils in 31-3 collected at ACRE in July, August, September, and October, 2004.

The SAC distances ranged from 2 and 8m with the majority being at 6m for the prairie soils and ranged from 6-10m with the majority being at 8m for the forested soils. The Moran's I ranged from 0.07 –0.38 and 0.11-0.52 for the prairie and forested soils, respectively. The Z-values ranged from 5.21-13.49 and 6.07-15.62 for the prairie and forested soils, respectively. The P-values were all significant for all measurements at the 0.001 level.

A time series of the spatial autocorrelations showed that there is local variablity in EC_a over time. Spatial cluster maps were also developed for each sub-field, but not shown here, using an exploratory analysis technique known as local indicators of spatial association (LISA) where a cluster is classified when the value at a location , either high or low is more similar to its neighbors than would be the case under spatial randomness (Anselin, 2005a) These maps showed significant changes from one time of data collection to another.

SUMMARY AND CONCLUSIONS

Due to the influence of the modifiable areal unit problem (MAUP), we chose not to interpolate point data into grids. Researchers must determine the optimal grid size for variables such as crop yield, EC_a estimates and soil nutrient test results before recommending this type of analysis. Therefore, this study made use of spatial process models based on spatial dependency and spatial heterogeneity. Apparent electrical conductivity was analyzed at two different locations in Indiana on nine different soils using three different transects 2.5 m, ≤ 10 m and 18 m by sub-field to determine the spatial-temporal stability.

At the DPAC site, spatial autocorrelation distance for the EC_a 0-30 and 0-90 cm depths varied widely depending on the sub-field and year that measurements were collected. The cause of this variation was related to differences in soil chemical properties not only between years but also among sub-fields. A time series showed an inverse relationship for the Moran's I in sub-field M1 between ECa depths of 0-30 and 0-90 cm. When tested by individual mapping units, there was only one soil (Saranac) that had a significant relationship ($P \leq 0.05$) with EC_a at the 0-30 cm depth. There were no significant results between individual soil mapping units and EC_a depth of 0-90 cm over the five years data that were collected.

The second part of this study was conducted in west-central Indiana on prairie and forest soils from July 19 through October 22, 2004 to assess spatial-temporal EC_a estimates. The results of spatial autocorrelation distance showed the sub-fields, which were 6 x 42 m in size, were stable at a distance between 2 and 10 m. But when one begins to examine the connectivity of the sub-fields in 131 (prairie soils) through cluster analysis one begins to see patterns shift from north to south and east to west. The sub-fields in field 31 (forest soils) were for the most part stable for both the spatial autocorrelation distance and cluster analysis. The exception was sub-field 31-3 where greater variability in spatial autocorrelation distance and cluster analysis was observed. The time series for field 131 showed that although spatial autocorrelation is significant for each of the three sub-fields Moran's I varied from week to week with sub-field 131-1 and with 131-3 Moran's I began high and had a decreasing trend while sub-field 131-2 beginning low and had an increasing trend. Sub-fields 31-1 and 31-2 showed a cyclic pattern and remained somewhat constant for the 13 week study. Sub-field field 31-3 began with a high Moran's I value and trended downward.

Diagnostics using OLS regression models determined the presence of spatial dependency spatial heterogeneity. Some weeks were significant for soil moisture, organic matter or K but the results were not consistent using either the OLS or spatial process models, and the causality relationship could not be established. Percent organic matter was greater in field 131 vs. field 31 but the OLS and spatial regression models showed more weeks with a significant relationship in field 31. The same was true for K/ kg ha^{-1} in that field 31 showed more weeks where EC_a estimates were significant vs. field 131. The reason for this is not known even though the literature often refers to the fact that soil moisture has an influence on EC_a values.

By employing spatial process models that test for spatial dependence spatial heterogeneity one could observe that the number of weeks with significant results was reduced. The reason for this is that if OLS models are employed without testing for spatial dependence spatial heterogeneity, one would be miss-specifying the correct model and thus would be susceptible to making the wrong conclusions.

An assumption was made that the soils in the study were representative of the eastern Corn Belt and if they aren't, measurements were made of these soils in such a manner that they accurately represented the soils within the study sites. Based on the analysis and the interpretation of the results, EC_a estimates using electrical conductivity instruments do not appear to be spatially or temporally stable or reflect the differences in soil moisture, organic matter, K or corn yield.

In order for farmers or researchers to utilize EC_a for soil moisture estimates, soil mapping, or fertility more work must be done to understand what EC_a is measuring and what is influencing the EC_a values under different controlled conditions. Based upon the results of our research, we conclude that apparent electrical conductivity (EC_a) does not provide consistent results for the measurement and/or assessment of soil moisture content, organic matter and potassium.

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