COMPARING GRID AND EC DIRECTED ZONE SAMPLING SCHEMES FOR SOIL FERTILITY MANAGEMENT IN FLORIDA

By

ASHLEY MASON

A THESIS PRESENTED TO THE GRADUATE SCHOOL
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LIST OF ABBREVIATIONS

Ca	Calcium
CEC	Cation Exchange Capacity
EC_a	Apparent Electrical Conductivity
EC	Electrical Conductivity
GNI	Grid No Interpolation
GWI	Grid With Interpolation
ha	Hectare
K	Potassium
Mg	Magnesium
pH	Acidity or Alkalinity
P	Phosphorous
RMSE	Root Mean Square Error
ZIA	Zone Interpolated All
ZP	Zone Polygon

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Ashley Mason

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Site specific crop management involves identifying spatial variability within a field, and using that information to implement efficient management practices. On the go measurement of soil electrical conductivity (EC) is one method of delineating management zones that seeks to improve upon the grid sampling method for nutrient management (Corwin and Lesch, 2005). However, the relationship between spatial variability of soil EC and crop nutrients is unclear (Johnson et al., 2001; Rysan and Sarec, 2008). In this project comparisons were made between grid and soil EC_a delineated zones sampling strategies for fertility management in peanut production. Our first objective was to relate soil chemical or physical properties to on-the-go measurements of soil EC. Our second was to compare grid and zone soil testing methods to determine which is most accurately characterizing nutrient variability. These included comparison of grid sampling by polygon, grid sampling with interpolation, zone sampling by polygon and zone sampling with interpolation. From our results we conclude that while EC_a variation existed within our fields, the variation in EC_a had no relation to soil factors of agronomic importance. We conclude that while EC_a zone soil

sampling for productivity management has proved appropriate in other locations with different landscapes and soil type, (Johnson et al., 2001; Kaffka et al., 2005; Kitchen et al., 2005; Sudduth et al., 2005) zone soil sampling using EC_a measurements is not an improvement upon the traditional one hectare grid soil sampling in Northwest Florida.

CHAPTER 1
INTRODUCTION

Cost for fertilizer and lime have increased dramatically in recent years, creating incentive for new strategies in fertility management. Soil sampling has historically been used to assess fertility needs while managing each field as a homogenous unit (Flowers et al., 2005). Yet considerable variability is known to exist within fields, which creates potential for over or under application of nutrients. Greater application efficiency may be achieved through site-specific nutrient management. Site-specific management utilizes rapidly evolving and available electronic information technologies to modify land management as conditions change spatially and temporally (van Schilfgaarde, 1999). In lieu of traditional soil sampling, which has historically been to treat fields as homogenous areas, grid soil sampling identifies within field nutrient variability and initiates nutrient application on a site-specific basis (Fleming et al., 2001). A grid size of one hectare (ha) is most prevalent in practice (Fleming and Westfall, 2000). However, research indicates that yield influencing soil variability is not captured in the typical grid size of one hectare. While smaller grids clearly better represent within-field variability, they are labor and cost prohibitive. There exists a need for nutrient assessment strategies that require fewer samples, yet generate effective field prescriptions for variable rate fertilizer applications (Johnson et al., 2001; Khosla,1999; Sadler et al., 1998). Zone soil sampling, an alternative to grid sampling, seeks to identify and manage within field variability in a site-specific manner. Zone sampling ideally reduces the number of samples per field, thereby reducing sampling costs while still obtaining within field nutrient variation information. For zone sampling to be useful, identification of agronomically relevant variability within fields is necessary. Efforts to identify and manage soil salinity levels in arid, irrigated soils prone to salinity issues have acted as a catalyst for the development of spatial technologies that easily obtain information about within field variability of soil properties. Corwin & Lesch (2003) note that soil salinity has typically been defined in terms of the electrical conductivity (EC) of a saturated soil paste extract (EC_e). A ‘paste’ of the sample is used because routine soil samples generally do not have enough moisture to perform the extraction, thus soil solution extracts are facilitated by adding water to the sample (Corwin & Lesch, 2003). The time, labor and capital for analysis of EC_e have encouraged exploration of alternative methods of obtaining field salinity information. Measurement of apparent soil EC (EC_a) is now a popular alternative to EC_e for use in identifying within field EC variation. ECa measures the conductivity of the soil profile within the measurement range, providing a sum value of conductance of the soil solution, solid soil particles and exchangeable cations (Corwin & Lesch 2003). Therefore while this measurement is used in lieu of the laboratory analysis of EC_e, it is actually analyzing the soil solution, solid and cations rather than the soil solution exclusively. Williams and Baker (1982) found in saline or salt-affected soils, 65–70% of variation in EC measurements could be explained by the concentration of soluble salts. However in non-saline soils, conductivity variations are mostly attributed to soil moisture, texture, and CEC variability (Williams and Baker, 1982). EC_a measurements may be obtained by either a four electrode system (Rhoades et al., 1990; Halverson and Rhoades, 1976), referred to as the wenner array, (Rhoades and van Schilfgaarde, 1976) or an electromagnetic-induction (EMI) system (Lesch et al., 2000). The four electrode system requires at least four electrodes be in contact with the soil, during which an electrical current is injected and the reduced voltage is measured

(Lund et al., 1999). This value is the soil apparent electrical resistivity. Corwin and Lesch (2003) note that in homogeneous mediums, resistivity is the reciprocal of conductivity. A resistivity device converts given measurements of apparent resistivity into measurements of apparent EC_a (Corwin and Lesch, 2003). The EMI system obtains EC_a data using a transmitter coil to create an electrical field between the transmitter and receiver coil, in which the response is measured (Lund et al., 1999). No contact is required between the receiving instrument and the soil; therefore EM measurements have an advantage of over the fixed four electrode array systems, which produces less reliable measurements in dry or stony soil (Corwin and Lesch, 2003). However the advantage of the mobilized fixed-array system includes equipment simplicity and speed of operation (Carter et al., 1993), which has led to its proliferation in practical field use. Veris Technologies in Salina, Kansas offers commercialized EC_a measurement equipment, among which is a series of mobilized fixed-array systems. These efficient tools for measuring EC_a are paired with global positioning system instruments to create manageable EC_a datasets. EC_a measurements are product of a complex interaction of soil properties (Corwin and Lesch, 2003). Soil properties that influence EC_a measurements include soil salinity, clay content and cation exchange capacity, clay mineralogy, soil pore size and distribution, soil moisture content, organic matter, bulk density, and soil temperature (McNeil, 1992; Rhoades et al., 1999a, 1999b; Corwin and Lesch, 2003). Previous studies relating crop yield directly to EC_a present inconsistent results (Corwin and Lesch, 2003), and the relationship between spatial crop nutrient variability and soil EC_a remains unclear. This is the premise of our comparison of grid soil sampling to EC_a directed soil sampling for fertility management in peanut production. Our objectives include relating soil chemical and physical properties to spatial measurements of soil EC_a. Our second objective is to compare grid and EC_a directed zone soil sampling to determine which most accurately characterizes spatial variability in soil chemical properties.

Literature Review

Grid soil sampling has been popularly adopted over the last decade to identify within field soil variability in effort to improve the efficiency of soil nutrient management compared to the traditional method of managing a field as a homogenous unit (Fleming et al., 2001). While a one-hectare grid is common, research indicates that yield influencing soil variability is not captured in the typical grid size of one hectare. Franzen et al., (1995) examined several grid sizes in effort to identify the density of sampling that most effectively identifies soil variability. Results from Franzen et al., (1995) suggest the use of 220 square foot grids for initially determining soil variability. Field-scale yield measurements by Sadler et al., (1998) found yield to be quantitatively different in distances as short as 10 m. While smaller grids clearly better represent within-field variability, they are labor and cost prohibitive. There is a need for management methods that require fewer samples, yet generate effective field prescriptions for variable rate fertilizer applications (Johnson et al., 2001; Khosla, 1999; Sadler et al., 1998). Strong incentive exists for growers to pursue these management methods that optimize their fertility programs in that variable rate fertility programs have the potential to improve input efficiency, field profitability, and environmental stewardship (Sawyer, 2013). For example, in a comprehensive examination of yield limiting factors in a 48 ha peanut production field in the Texas High Plains, Färe et al., (2009) found Calcium and Nitrogen to be most limiting to yield. By recognizing and managing these limiting factors with variable rate fertilizer application, Färe et al., (2009) reported a savings of \$20.41/ha in N and \$10.73/ha in Ca as compared to the projected expenditures of a conventional fertility program.

The clear limitation of the ability of grid sampling to capture within field variability in a cost effective manner has stimulated interest in managing within field variability by separating fields into areas of homogenous characteristics. This alternative to grid sampling seeks to create within-field management zones by identifying homogenous sub-regions that possess characteristics that may limit, or relate to yield limiting factors (Vrindts et al., 2005). Assuming generation of useful zones is achievable; this would allow field inputs to be managed more efficiently, ideally saving time and money, affirmed by Fleming et al (2000). Multiple methods are available for assessing in-field variability. Yield data, when collected over multiple years, can be used to identify homogenous zones of crop productivity (Blackmore, 2000; Fraisse et al., 2001). Research conducted by Fleming et al., (2001) concluded that zone management by a combination of aerial photographs, soil color, topography, and grower field knowledge, creates prescription maps that are equally effective as variable rate maps generated from grid sampling. Topography and soil characteristic data utilized by Reyneirs et al., (2006) successfully created critical zones for yield variation in response to erosion risks. Additionally, Zone Mapping Application for Precision Farming (ZoneMAP) is a tool accessible online which provide users access to archives of satellite imagery data. This tool uses the fuzzy c-means (FCM) algorithm for generating management zones for given fields; ZoneMAP also has the capacity to determine the optimal number of zones based on the archived data for a given field.

Li et al., (2008) found the combination of soil electrical conductivity measurements, yield, and normalized difference vegetation index (NDVI) data to accurately characterize spatial variation of soil chemical properties and productivity in cotton. Research completed by Nanna and Franzen (2003) concluded that there are various means of assessing field variability, and that consistency should be valued over high correlations. One year of their study delineating nitrogen management zones found that Order 1 soil survey maps highly correlated with field nitrogen management needs. However in years to follow the soil survey maps did not perform consistently in comparison to zone delineation by topography, yield and NDVI from satellite images.

The need for performance consistency and collection efficiency has stimulated interest in zone delineation by apparent soil electrical conductivity (EC_a) measurements. Soil EC_a is a relatively inexpensive measurement when collected using sensor based technology. Electrode-based EC_a sensors have been used to explore soil variability for several decades and are commercially available today. One of the earliest forms of the electrode based sensor was used to measure and map soil salinity in the late 1970's (Halvorson and Rhoades, 1976). It was later adapted for mobile use by mounting the electrodes on a tractor and connecting to a GPS receiver and data logger (Carter et al., 1993). The device was then commercialized in 1999 by Veris Technologies (Lund et al., 1999). These electrode-based sensors require soil contact, and the current equipment typically uses a set rolling coulters. The Veris 3100 (Veris Technologies, Salina KS) has six rolling coulters that provide two continuous spatially referenced measurements of EC_a. Depth of measurement is determined by the spacing of the coulters, the larger the spacing the deeper the measurement (Corwin and Lesch, 2003). Of the six coulter electrodes, coulters number 2 and 5 are the current producing electrodes, (Corwin and Lesch, 2003) while the others receive the electrical charge. These two sets of electrode arrays allow for simultaneous measurement of EC_a at two soil depths: 0 to 0.3 m and 0 to 0.9 m (Corwin and Lesch, 2003). Previous reports have described the theory and principles behind measurement of EC_a (Corwin and Lesch, 2003; Friedman, 2005). The injected current for measuring EC_a using the Wennar array fixed coulter method travels in three pathways within the soil. These include a liquid phase pathway via dissolved solids contained in the soil water occupying the large pores, a solid–liquid phase pathway primarily via exchangeable cations associated with clay minerals, and a solid pathway via soil particles that are in direct and continuous contact with one another (Rhoades et al., 1999). The resulting value of the received electrical charge after traveling through the soil profile provides the soil resistivity. Burger (1992) notes that when measured with the Wennar array the formula for resistivity (p) is:

$$p=2\pi a\Delta V/i = 2\pi aR \qquad (1\text{-}1)$$

Where V is the voltage, a is the interelectrode spacing, i is the electrical current, and R is the measured resistance. Being that EC_a is the inverse of R, for useful purposes this equation becomes:

$$EC_a= 1/2\pi aR \qquad (1\text{-}2)$$

Soil solution salinity, quantity of exchangeable ions associated with clay particles, and soil particles in direct contact within the zone of measurement all influence EC_a readings. Williams and Baker (1982) found in saline or salt-affected soils, 65–70% of variation in EC measurements could be explained by the concentration of soluble salts. However in non-saline soils, conductivity variations are mostly attributed to soil moisture, texture, and CEC variability (Williams and Baker, 1982).These factors are then influenced by a combination of soil physical and chemical properties, including but not limited to; soil water content, bulk density, clay mineralogy and content, organic matter, and soil temperature (Corwin and Lesch, 2005; Rysan and Sarec, 2008). In general, sands have a low conductivity and will thus influence ECa measurements to be lower, while silts have a medium conductivity and clays have a higher conductivity (Lund et al., 1999). Because of within field variability of soil properties, correlation between EC_a and specific soil properties may be quite different from field to field (Corwin and Lesch, 2003). Additionally, soil and environmental conditions and methods employed during collection of EC_a data can also influence measurements (Sudduth et al., 2005).

Soil electrical conductivity has not been found to have a consistent or direct relation to crop yield, (Rysan and Sarec, 2008; Johnson et al., 2003) However, EC_a measurements have been found to relate to soil physical and chemical properties that impact yield. This is why, as outlined in the compilation of survey protocols by Corwin and Lesch (2005), ground truth samples within EC_a delineated zones are a crucial component for the creation of EC_a directed prescription maps (Johnson et al., 2001). In research conducted by Johnson et al. (2001) soil samples from EC_a directed management zones were analyzed for correlation with EC_a. Percent clay, bulk density, pH and $EC_{1:1}$ was all found to have a positive correlation with the EC_a readings. Soil moisture, total and particulate organic matter, total C, total N, microbial biomass carbon and microbial biomass nitrogen were negatively correlated with EC_a. Collected surface crop residue was significantly related to EC_a zones, and negatively correlated with EC_a.

Johnson et al (2001) thus concluded that soil classification by EC_a is an effective basis for delineating field management zones. Sudduth et al. (2003) analyzed the relationship of certain soil properties to EC_a in four fields, and found soil moisture to be correlated with EC_a in only one field. Clay and CEC were correlated with EC_a in all studied fields (Sudduth et al., 2003). Regarding yield influencing nutrients, Heiniger et al. (2003) found few significant linear relationships between EC_a and soil test levels of P, K, Ca, Mg, Mn, Zn or Cu. In the instances which a statistically significant relationship existed, if was often weak with an R^2 less than .50. Heiniger et al (2003) identified a few instances of stronger significant relationships between ECa and soil nutrients, in which the R^2 was between .51 and .75, and found this occurred when the nutrient was also closely associated with one of the soil properties that directly influence EC_a. From this analysis Heiniger et al. (2003) concluded that, "It is unlikely that EC_a can be used to directly determine soil nutrient content across a field. However, EC_a, can be used along with other measured soil properties in a multivariate analysis to describe key factors influencing changes in nutrient concentrations and to establish nutrient management zones." Here Heiniger et al. (2003) note that it is important when using EC_a measurements to establish management zones, to know and account for site-specific changes in volumetric soil moisture content, soil texture, CEC and salinity. In an analysis of the usefulness of zones established by EC_a values obtained by EM, Taylor et al., (2003) found the zones to be closely correlated with soil series maps and related to yield variations in instances where there existed large difference in soil textural classes.

Following collection of EC_a data, various procedures can be used to delineate management zones. The first step is to interpolate vector (point) EC_a data to produce a raster image, or matrix of grid cells representing the surface of the field. Various options for interpolation exist. McCoy and Johnston (2001) identify two groups of interpolation techniques in ArcGIS (ESRI, city, state) spatial analyst. These include deterministic and geostatistical. Deterministic is defined as using mathematical functions for interpolation, while geostatistical is defined by use of statistical and mathematical methods. Inverse Distance Weighting is a deterministic interpolator, while krigging is a geostatistical interpolator. Inverse Distance weighting operates with the assumption that points close to each other are more alike than points further apart. Values determining unknown points are weighted based on their proximity to the unknown point. There are various kinds of geostatistical interpolators; however they are all related to kriging. Kriging also uses the same assumption as IDW, however includes the use of statistics. Kriging quantifies the study area by fitting a spatial dependence model to the data. To make predictions, kriging uses the fitted model, spatial configurations, and values at measured sample points near the prediction location (McCoy and Johnston, 2001). There are three steps required for successful Kriging. These are described in O'Sullivan and Unwin (2010) and include: "1.) Producing a description of the spatial variation in the sample control point data. 2.) Summarizing this spatial variation by a regular mathematical function. 3.) Using this model to determine interpolation weights."

Step one is accomplished by creating a semivariogram in attempt to understand the spatial variability. O'Sullivan and Unwin (2010) describe a semivariogram as "an application of exactly the same idea of control point data, with the additional provision that we wish to estimate its value at a series of distances."

The equation for creating a (semi)variogram is given by O'Sullivan and Unwin (2010) as

$$2\hat{y}(d)= 1/n(d) \quad \text{sum of } dii=d \quad (zi-zj)2 \qquad (1\text{-}3)$$

The right side of the equation refers to the sum of squares of all the pairs of control point values at a given distance (d), divided by the total number (n). On the left side of the equation, $\hat{y}$ indicates that we are estimating distance, and the 2 is from the development of the semivariogram idea by George Matheron, French geostatistician in 1963. Important language describing complexities of semivariograms include the notion of a nugget, lag, sill and range. 'Nugget' refers to the errors of measurement and spatial variation that are below the shortest sampling interval in the dataset. 'Lag' is a term to describe the spacing of data points in the semivariogram. The 'sill' is defined as the point at which semivariance is the highest. The distance at which semivariance is the highest is described as the 'range' (O'Sullivan and Unwin 2010). The range is the extent to which influence is expected to occur for a given data point. O'Sullivan and Unwin (2010) explain that this step is what distinguishes Kriging from IDW, in that it makes use of what is understood, or can be inferred, about the spatial structure of the existing control data. This theory was developed by Georges Matheron in 1963, and was a product of methods used in South African mining by Dani Krige. O'Sullivan and Unwin humorously describe the step of estimating an appropriate mathematical function to model the semivariogram as a "black art", in that it requires careful analysis and familiarity with the variable in question, and specify that this is not a step that can be accomplished solely by a computer program. O'Sullivan and Unwin (2013) specify that in preparing a semivariogram, there exist the need for some arbitrary decision making, like distance intervals and nugget values. While an educated decision is optimal, Chiles and Delfiner (1999) stated that a crudely determined set of weights can provide excellent results when interpolating a dataset. The next step is computationally intensive, in which the selected model is used to interpolate the control data points, with the assumption that variation is a function of distance (O'Sullivan and Unwin, 2013).

In research completed by Robinson and Metternich (2006) inverse distance weighting, ordinary kriging, lognormal kriging, and splines were compared for interpolation accuracy of seasonally stable soil properties. Robinson and Metternich (2006) defined seasonally stable soil properties to include pH, electrical conductivity, and organic matter. To compare the different interpolation methods, Robinson and Metternich (2006) used cross validation to examine the differences between known and predicted data points. Cross validation assesses the accuracy of an interpolation method by eliminating known information, allowing the interpolation to predict the missing value, and computing the difference between the known and predicted value. The root mean square error values, average kriging standard error, root mean square standardized prediction error, and mean standardized prediction error values were considered. Their results indicated that ordinary kriging performed best for topsoil pH, and lognormal kriging provided the best results in EC_a interpolation. In their study IDW best predicted subsoil pH. The spline method best predicted soil organic matter (Robinson and Metternich 2006). In summary of this point, cross validation is a common and reliable way to assess the success of an interpolation method exercised in a specific dataset (Voltz and Webster 1990).

Following interpolation of EC_a data, values are typically classified into groups (zones) that minimize variability within the group and maximize variability between the groups. There are various ways this can be accomplished. Frigden et al. (2004) developed a software package that uses fuzzy c-means unsupervised clustering to delineate potential management zones. Fraisse et al. (2001) also used an unsupervised clustering algorithm, ISODATA (Iterative Self-Organizing Data Analysis Technique); referred to as the ISOCLUSTER function in the Arc/Info GIS software to create management zones from EC_a and yield data. ISOCLUSTER uses a modified iterative optimization procedure, or migrating means technique. Arbitrary means are assigned by the software per user defined cluster; each cell is then assigned to the closest of those means. Means are recalculated for each cluster based on the distances of cells belonging to the cluster after iteration, and the process is repeated until the movement of cells from one cluster to another. The repetition of mean recalculation is called an "iteration", which the user may specify, in addition to the number of desired classes, minimum cells and sampling interval (Fraisse et al., 2001). In creation of management zones using EC_a data, Johnson et al (2003) interpolated the EC_a data using IDW with the nearest-neighbor technique. The resulting maps were reclassified into four management zones. Additionally, Lesch et al. (2000) developed a software package (ESAP) which identifies optimal location for zone sampling sites from EC_a data, using a response surface sampling design. This software is available through the USDA Agricultural Research Service. Johnson et al (2001), in evaluation of zone soil sampling, assigned sampling points to “non-adjoining areas of each zone”, with the goal being to “provide comprehensive coverage of the experimental site”. This appears to be the most common method used in practical EC_a zone sampling situations. It is clear that various mathematical techniques can be applied to determine the number of management zones assigned to a particular field. However, in many commercial situations the number of zones used is often arbitrary and may lack agronomic significance.

Although various methods exist for collecting and processing spatial data to establish soil sampling procedures, the goal of our study is to assess the performance of grid and zone soil nutrient management on Florida soils using methods currently in use for fertility management in Florida. Researchers have used various strategies for quantifying differences in grid and zone soil test data. Flowers et al. (2005) compared yield-based management zones to three grid sampling methods. Zones were generated by culminating the previous four years yield data into one raster. Management zones were created using four strategies. Three of the strategies yielded maps with 20 by 20 meter spatial management units. The fourth method allowed larger zones, more appropriate for practical use. Their grid sampling methods included grid cell, grid center, and grid center with kriging. The grid cell method uses the mean value of all data points contained within the respective grid. The grid center method used the value of the data point nearest to the center of the grid. Grid center with kriging took the value of the data point nearest to the center of the grid and interpolated it using kriging.

Control regions were constructed by randomly dividing each field into areas of equal size and number related to the grid sampling and yield based zone methods. For each assigned control region, fertilizer recommendations and mean soil test P, K and pH values were calculated. Flowers et al. (2005) note that a method of determining if the residual variance of two treatments is statistically difference is not available. Therefore, to compare the sampling strategies residual variance to the variance of the corresponding controls, Flowers et al. (2005) concluded a difference of 15% signified that the treatment data was a result of the sampling scheme, not density of sample data.

Additionally, a whole field soil test value was generated from the mean of all data points available in each field. This yielded separate whole field values for soil test P, K and pH, and recommendations for P, K and lime applications. These values served as the baseline to which the sampling schemes were compared to, in that the whole field average method was assumed to generally have the highest residual variance. The mean value for each field was then

Weighted variances for each sampling scheme were calculated and compared to the whole field average method described earlier. The values found for the whole field average method were considered to be 100% variance. The residual variances of the sampling schemes were found by comparing weighted variance to the 100% variance value. Their results indicated that the 68 meter grid cell sampling method best captured within field nutrient variability.

Mallarino and Wittry (2004) exhibit another method of comparing data from grid and zone soil sampling. Management zones were determined in such a way that integrated soil survey map information, elevation data, yield, information from aerial photographs and grower experience. Grids were created by systematic arrangement of cells ranging 1.2 to 1.6 hectares in size. The baseline for comparison was created by soil test values derived from a 0.2 hectare grid sampling scheme. An index of efficacy was created for each sampling method. Within group variability was compared to between group variability. Higher between group variability suggests a successful sampling scheme, whereas higher within group variability can be assumed product of a flawed sampling design. Additionally, P and K fertilizer recommendations were generated for each sampling approach. By comparing the fertilizer recommendations for the intense 0.2 hectare sampling data to the other sampling methods, Mallarino and Wittry (2004) were able to determine the field proportion that would be correctly, over, and under fertilized for each method. Their results indicated that grid cell and zone sampling strategies best identified within field nutrient variability when compared to methods using exclusively soil survey maps or elevation zones. Additionally, Fleming et al. (2004) used analysis of variance (ANOVA) to compare nutrient and yield sample data between zones delineated by EC_a and soil color with farmer input. They found EC_a to be more useful in identifying areas of spatial variability within fields.

Materials and Methods

The study site was located at the West Florida Research and Education Center in Jay, Florida (30.78, -87.14) and used seven fields, four in 2012, and three in 2013. All fields were in a peanut-cotton rotation. The most common soil type among the seven fields was Red Bay Sandy loam and Lucy loamy sand (Table 1-1.).

Peanuts were grown in each field during their respective year of study. In March of 2012 and 2013, a grid size of 1 ha was assigned to each field using Farmworks® software (Hamilton, IN) installed on a Trimble® Nomad® handheld computer. Soil EC was collected using the Veris 3150 sensor cart (Salinas, KS). The Veris 3150 traversed each field at an 18.3 m swath width, collecting on average one data point every 6.2 meters. Shallow EC_a measurements were continuously collected from 0 to 0.3 m depth of soil and were be used to generate three management zones for each field. Management zones were delineated in Agjunction.com by interpolation of the EC_a measurements to create a raster file that was classified into three zones using a clustering algorithm (proprietary information was unavailable). The use of three zones was pre-determined and considered to be consistent with the number of zones that are typically used by growers given logistical and financial restraints. Soil from the four peanut production fields (3 to 14 ha) was sampled in March of 2012 according to grid and soil EC_a directed management zones prior to tillage, fertilizer, lime and planting operations. This was repeated for the three fields (4.5 to 8.5 ha) in 2013 with sampling occurring in March.

Following delineation of zones and 1 hectare grids for each field, soil samples were collected and sent to Waters Agricultural Laboratories (Camilla, Ga) for analysis. Analysis included pH, texture and Mehlich 1 extractable P, K, Ca, and Mg. Grid samples were derived from a composite of 8 cores (15 cm depth) collected from within 3 m radius of the center of each grid. The Trimble® Nomad® handheld computer was used to locate sampling points at the center of each grid. Zone composite samples were derived from a minimum of 8 cores (15 cm depth) collected from random locations from within each zone. Random soil core locations selected for zone composite samples were spatially referenced, sampled and analyzed independent of the composite sample. Software is available for identification of optimal sampling locations within each zone, however to mimic practical sampling scenarios we randomly choose sampling locations with the objective of capturing variability within each zone.

Following collection of soil samples, uniform application of P, K and lime were applied to whole fields according to grid or zone recommendations in 2012 and grid recommendations in 2013. (See Table 1-2 for average P, K and lime applications) In 2012 and 2013, lime and fertilizer was incorporated by shallow tillage and seedbeds were prepared on 91.4-cm centers. Prowl H2O (pendimethalin: N-(1-ethylpropyl)-3,4-demethyl-2,6-dinitrobenzenamine) was applied pre-plant at a rate of 0.63 kg ha^{-1}. Peanut, ‘Georgia 06G was seeded in early May of 2012 and 2013. Additional weed and pest control was applied as needed according to IFAS guidelines. Peanuts were inverted and field dried for 3-5 days before threshing. Yield was determined by harvesting and measuring fresh weight of five meters of two parallel rows centered over each georeferenced zone and grid sample point.

One-way ANOVA with comparison of means with Tukey-Kramer HSD in JMP was used to determine difference in soil variable levels by field and year. ArcMap 10.0 was used for mapping, interpolation and analysis of soil nutrient data. Kriging and

Inverse Distance Weighting interpolation methods were implemented using all soil sampling points (grid and zone combined) and compared based on cross validation of known sample values to predicted values of soil parameters, including pH, and Mehlich 1 extractable P, K, Ca, and Mg. The best interpolation method was determined by selecting the method that provided the smallest root-mean-square prediction error, a root-mean-square standardized prediction error value closest to 1 and a mean prediction error near 0. Ordinary kriging was selected as the method providing the lowest root mean square error. Ordinary kriging model was selected for each nutrient by the model which provided the lowest RMSE (Robinson and Metternicht, 2006). The selected map, or control map, was used as a best estimation of variation of soil nutrients within each field. In addition, interpolation was used to generate the treatment raster maps of soil parameters using grid center points (grid point), 1 ha grid polygons (grid polygon), composite values assigned to the entire zone (zone polygon), and interpolation of all zone points (zone interpolated all). Examples of EC_a data found in Figure 1-1, Example of EC_a zones found in Figure 1-2, Example of 1 ha grid polygon found in Figure 1-3. Known versus predicted nutrient values were compared for the purpose of determining if the efficacy of interpolation was impacted by our sample distribution and density. Known sample values for P, K, Mg, and Ca were compared to the predicted value of the same spatial location after interpolation. This predicted value was obtained from the interpolated nutrient rasters by using the ArcMap10 spatial join function with the initial soil test point file. The known and predicted nutrient values were compiled for each field and separated by grid or zone treatment and analyzed using a t-test in JMP Pro 10.

Linear and quadratic regression analyses in JMP Pro 10 were used to identify relationships between soil chemical and physical properties and their corresponding EC_a and yield values. Soil test variables lacking normality were given a log10 transformation. Regression equations were considered significant when $p < 0.05$ and coefficient of determination (R^2) was reported.

EC_a data was evaluated in SPSS using a univariate one-way analysis of variance with LSD for separation of means. This evaluation identified the presence or lack of statistical difference between EC_a values between management zones. Amount of variation between zones may explain success or lack of the management zones ability to identify variation related measured nutrients. Similarly, mean values for P, K, Ca, and Mg were compared across management zones for each field.

Accuracy of the four treatment methods was assessed by comparison to the control raster. The control raster for each field was generated by optimally interpolating all available data points. Control and treatments rasters were then standardized by (raster values-mean)/raster standard deviation.) These maps were converted to integer maps for their use in the spatial analyst – map algebra tool in ArcMap 10. The Map algebra tool was used to calculate the absolute difference between each field's standardized control and standardized treatment raster maps derived from grid or zone sample points for P, K, Mg and Ca. The resulting difference raster maps were compared based on the percent area that was predicted within 1 standard deviation (1SD) of the intensively sampled control (Berry, 2011).

Treatment method accuracies were further compared using a 10 x 10 meter subsampling method. This was accomplished by first creating the 10 x 10 grid shapefile using the grid index features tool in ArcMap 10. Selected field border was specified as the extent. Each previously generated treatment and control raster for P, K, Ca, and Mg were converted to an integer raster; means from each integer raster were extracted using the Spatial Analyst- Zonal- Zonal Statistics tool in ArcMap 10, specifying the grid file for extraction of means from the raster. Resulting file was converted back to an integer file and converted to a polygon. Data from attribute table was exported to excel to be analyzed in SAS. Analysis was completed using PROC glimmix with adjustment for location considered by specifying location in random residuals. P and t values were considered from Least Squares Means Dunnett Adjustment for Multiple Comparisons. $P < 0.05$ was considered significant and indicated the treatment is statistically alike the control.

Table 1-1. Percent soil type by field characterized by USGS soil survey map

Soil Type	Field 1	Field 10	Field 14	Field 18	Field 19	Field 20	Field 21
Dothan fine sandy loam	8.50%		32.60%				
Orangeburg sandy loam	19.20%	3.20%		24.90%		0.60%	
Red Bay sandy loam	72.20%	57.80%	57.90%	1.20%	30%	54.40%	93%
Dothan fine sandy loam		39.90%		7.20%			
Tifton sandy loam		2.20%					
Lucy loamy sand				21.60%	49.90%	35.80%	7%
Fuquay loamy sand			9.50%	45%		0.30%	
Troup loamy sand					20.10%	8.90%	

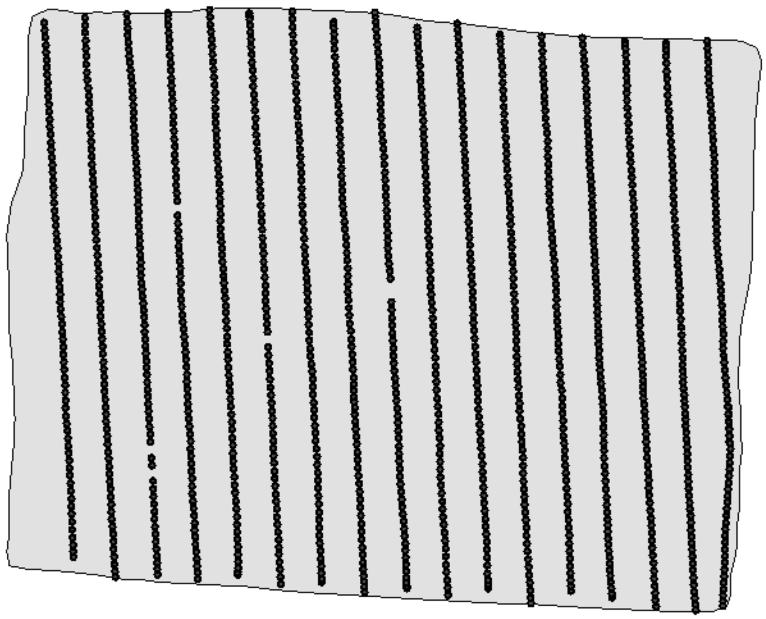

Figure 1-1. Example of EC_a data points collected by the Veris 3150 sensor cart, field 21 prior to interpolation.

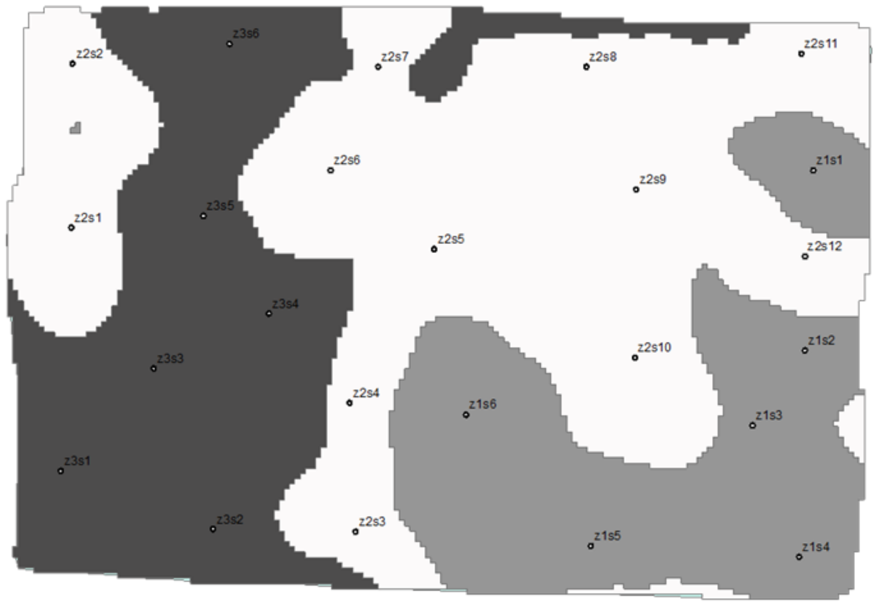

Figure 1-2. After interpolation of EC_a points, the maps were reclassified into three classes. These classes indicated three management zones consisting of low, medium and high EC_a zones. Within these zones points were placed where soil samples were taken to capture variability within each zone.

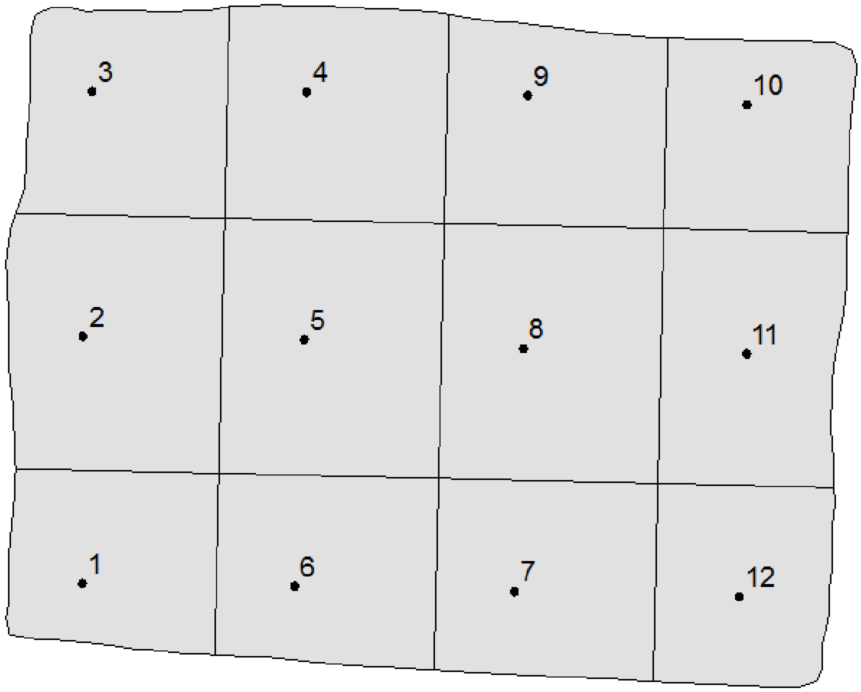

Figure 1-3. Grid samples sites were identified by overlaying a one hectare grid on each field. Soil samples were taken from the middle of each grid.

Table 1-2. Average fertilizer and lime application per hectare for all study fields

Fertilizer and Lime kg/ha	1	10	14	18	19	20	21
Lime	2501	2224	1406	1098	1937	1341	1489
DAP (18-46-0)	130	118	108				117
Rainbow/Bonanza (5-15-30)				378	396	384	

CHAPTER 2
RESULTS

Field Level Soil Chemical and Physical Properties

Analysis of soil for four fields in 2012 and three fields in 2013 revealed differences in soil nutrient levels, CEC, and texture across fields. Mean soil chemical and physical properties for whole fields were derived from averages of all sampling points for each field. Soil test values for P, K, Ca, Mg, and CEC and soil texture were found to differ across fields (Table 2-1). Variability in extractable soil nutrient concentration, CEC, and texture within and across fields revealed scenarios where site-specific management could be beneficial.

The IFAS Soil Testing Laboratory has determined critical values for P, K, Ca, and Mg required for peanut production (Adams et al., 1994). Average concentration of Mehlich 1 extractable P for all sample points in each field ranged from 9- to 66- mg kg^{-1}. Soil test P was 46% greater ($p < 0.05$) in field 20 compared to fields 14, 18 and 21. Fields 1, 10 and 19 had similar soil test P levels ($p > 0.05$) and were below critical values for peanut production (30 mg kg^{-1} Mehlich 1 P) (Adams et al., 1994). Mehlich 1 extractable K concentration ranged from 35- to 105- mg kg-1 for all fields. Soil test values for K were greater ($p < 0.05$) in fields 10 and 14 while fields 19 and 20 had the lowest concentration of extractable K. Fields 1, 18, 19 and 20 were below critical values (60 mg kg-1 Mehlich 1 K) for peanut production (Adams et al., 1994). Concentration of Mehlich 1 extractable Mg was highest in field 10 at 133 mg kg-1 and variability did exist among fields. However, soil test values for Mg ranged from 64- to 133- mg kg-1, all above the critical value (30 mg kg-1 Mehlich 1) for Mg indicating yield response to fertilizer nutrients are unlikely. Similarly, Mehlich 1 extractable Ca values ranged from

384- to 670- mg kg-1, all above the critical value (250 mg kg-1 Mehlich 1 Ca) for peanut production.

In addition to variability in soil extractable nutrients, soil CEC and texture could influence EC_a measurements and peanut yield. All fields had a mean CEC value below 8 meq 100 g-1, and is common for coarse textured soils. CEC was greatest ($p < 0.05$) in field 10 (7.19 meq 100 g-1), the lowest ($p < 0.05$) in field 19 (3.19 meq 100 g-1). Similar to CEC, variation in soil texture was observed among fields. Field 10 had greater ($p < 0.05$) silt and clay content compared to other fields, as was reflected in the measurement of CEC.

The coefficient of variation (CV) by field for soil chemical and physical properties is a good indication of within field variability. Overall, variation in soil nutrient content and CEC within fields was greater than variation of texture within fields. Considerable variability was observed for soil test P concentration, with CV ranging from 26% to 76 %. Similar high CV's were observed for K (15 – 47%), Ca (27 – 76%) and Mg (17 – 83%). The presence of within field variability of soil nutrient content was expected to provide the necessary environment for evaluating site-specific nutrient management practices and comparison of grid and EC_a-based zone management techniques.

Measurement of Soil EC_a

Spatial measurement of soil EC_a was completed using the Veris 3100 for each field and a clustering algorithm was used to divide each field into three distinct management zones. Soil EC_a values averaged by field ranged from 0.59 to 2.48. In addition, EC_a values were greater ($p < 0.05$) for fields measured in 2012 compared to 2013. Yet, differences in mean EC_a values between fields sampled during the same year were not detected ($p > 0.05$).

Although EC_a values averaged for whole fields did not differ among fields, mean ECa values did differ ($p < 0.05$) across the three management zones for each field (Figures 2-1 through 2-7). The clustering algorithm used by AgJunctions's commercial software to delineation zones was effective in separating fields into three statistically distinct EC_a-based zones. Establishment of three zones based on differences in EC_a was necessary to evaluate zone-based soil sampling schemes and to compare the method to alternative approaches.

Validation of Sampling and Interpolation Techniques

Following delineation of zones, soil was sampled according to grid-based or zone-based patterns. Whole field averages for soil nutrient concentration and texture derived from grid and zone based sampling schemes were compared using a t-test. Grid and zone sample nutrient means were significantly different by field ($p < 0.05$) in field 1 for Mg and Ca, field 20 for K, field 18 for P and field 21 for Ca and Mg. Similar to analysis of mean values from sample points, comparison of known versus interpolated points was performed for grid and zone sampling schemes. No difference in means for any field were detect for soil test values estimated by interpolation for each sampling scheme ($p > 0.05$). Similarity between whole-field grid and zone sampling schemes for measured and interpolated values was expected to reduce bias of control maps.

Relating EC_a to Soil Properties

Regression analysis identified weak and inconsistent linear relationships between EC_a and soil nutrients, CEC and texture (Table 2-2.). Non-linear relationships were not observed for EC_a and any of the measured soil properties. Significant linear relationships ($p < 0.05$) between soil test P and EC_a were observed in 4 of the 7 fields. Yet, relationships were weak in 3 of the 4 fields with $R^2 < 0.26$. Field 10 had the only strong (R^2 = 0.49) linear relationship between EC_a and P. Similar, significant linear relationships ($p < 0.05$) were observed for EC_a and soil test K in 4 of the 7 fields, although the relationships were weak ($R^2 < 0.25$). Relationships of EC_a with other soil test nutrient values measured were weak ($R^2 < 0.30$) and inconsistent across fields. Summary of the regression information is found in Table 2-2. An example the linear regression of P and EC_a is provided in Figure 2-8.

A relationship between EC_a and soil texture was observed in only 2 of the 7 fields used in the study. Fields 19 and 21 had weak ($R^2 < 0.33$) but significant ($p < 0.05$) linear relationships for sand, silt and clay and EC_a. Similarly, soil CEC was found to have a significant yet weak (R^2 = 0.13) relationship to EC_a in only 1 of the 7 fields. An example of the linear regression between soil EC_a and percent sand is provided in Figure 2-9.

Soil Properties and Yield by Zone

Soil properties were compared across EC_a-derived zones for each field. Differences in concentration of soil test nutrients and soil texture by EC_a zones ($p < 0.1$) were found in field 1 for P, field 10 for P and Ca, field 14 for P and K, field 21 for P and Mg. No differences were found in P, K, Mg or Ca by zone for fields 18, 19 or 20. Means separation revealed that differences occurred between only two of the three zones for all fields in which differences by zone were indicated (Table 2-3) In field 1 differences of sample values between two of the three zones existed for texture variables and P, with P values being 28, 20 and 17 mg/kg respectively, all below the critical value for P (30 mg kg^1). In field 10 variables % sand, % silt, CEC, P and Ca were different between two zones, with P values 27, 12 and 18 respectively, again all below the critical level for peanut production. Ca was 584, 812 and 603 mg kg^1, all zones being above critical Ca peanut levels (250 mg kg^1). In field 14, differences between zones were indicated to exist for K, in which zone 1 was different from zones 2 and 3, however zones 2 and 3 are not different. In field 21, differences between zones were indicated for variables: % silt & clay, % sand, % clay, % silt and P in two respective zones, with P values being 56, 43 and 45, all above critical levels (30 mg kg -1). In field 18, no differences were found between soil variables by zone. In field 19, differences between zones were indicated for: % silt &clay, % sand and CEC in two respective zones. In field 20 no differences were indicated between zones.

Yield was measured at each sampling location and yield was compared among and within fields. (Table 2-4) Field 19 was the highest yielding, with a field average of 6,757 kg/ha. Similar to soil test nutrient values, yield differences were not detected across zones ($p > .05$), with the exception of fields 19 and 20, in which yield was different ($p < .05$) in two of three zones.

Evaluating Grid and Zone Sampling Techniques

An example of the resulting output from the subtraction of standardized control from treatment is provided in Figure 2-10. Results from the subtraction of standardized control rasters from standardized treatment raster's are summarized in Table 2-5. Maps generated from the contrasting sampling schemes for P predicted 92 to 95% of the field area within 1SD of the control maps. The four methods predicted 91 to 96% of the field area within 1SD of the control for K, 83 to 95% for Ca, and 87-93% for Mg. Yet, no difference ($p > 0.10$) among methods was detected when comparing treatment to control maps for individual nutrients.

However, standardization of P, K, Ca, and Mg levels for each field allows observations of all nutrients to be pooled for comparison of sampling methods. Comparison of methods using pooled standardized nutrient maps revealed differences among methods (Figure 2-11). Grid with interpolation and zone with interpolation sampling schemes resulted in greater ($p < 0.10$) field area within 1 standard deviation of the control map compared the zone-polygon scheme.

In the analysis comparing 10 x 10 meter subsamples from each map generated by the contrasting sampling methods and control maps, some differences in sampling methods were observed. For soil test P, only ZP was similar to the control ($p<0.05$) (Table 2-6). ZIA and ZP predicted soil test K values similar ($p<0.05$) to the control. ZIA predicted Ca similar to the Ca control, and GWI predicted Mg similar to the Mg control ($p<0.05$). Means from treatment and control methods are summarized in Table 2-7. Besides the aforementioned results, all treatment 10 x 10 meter subsample results differed from the control ($p >0.05$).

Table 2-1. Mean and standard error from all available field soil samples, representing the average and variability in our nutrients and texture properties. P, K, Mg and Ca represent Mehlich 1 extractable nutrients.

	mg kg^{-1}								%						meq/100g	
Field	P		K		Mg		Ca		Sand		Silt		Clay		CEC	
	Mean	SE	Mean	SE	Mean	SE	Mean	SE	Mean	SE	Mean	SE	Mean	SE	Mean	SE
1	24	1.8	52	1.7	74	4.2	585	21	80	.6	11	.6	10	.3	6	.2
10	20	2.7	105	5.4	66	4.3	670	39	63	1.4	37	1.7	20	1.7	7	.4
14	44	4.2	89	5.1	78	5.5	597	35	82	.7	11	1.2	7	.6	6	.3
18	40	3.4	51	2.3	73	6.8	552	26	82	.6	13	.8	6	.3	5	.2
19	23	2.5	35	2.3	83	9.5	423	19	85	2.3	11	.7	7	.4	3	.3
20	27	6.7	47	1.8	127	9.5	482	22	84	.5	10	.8	6	.5	4	.2
21	49	2.2	67	2.5	80	6.1	384	55	81	.6	11	.9	8	.5	6	.2

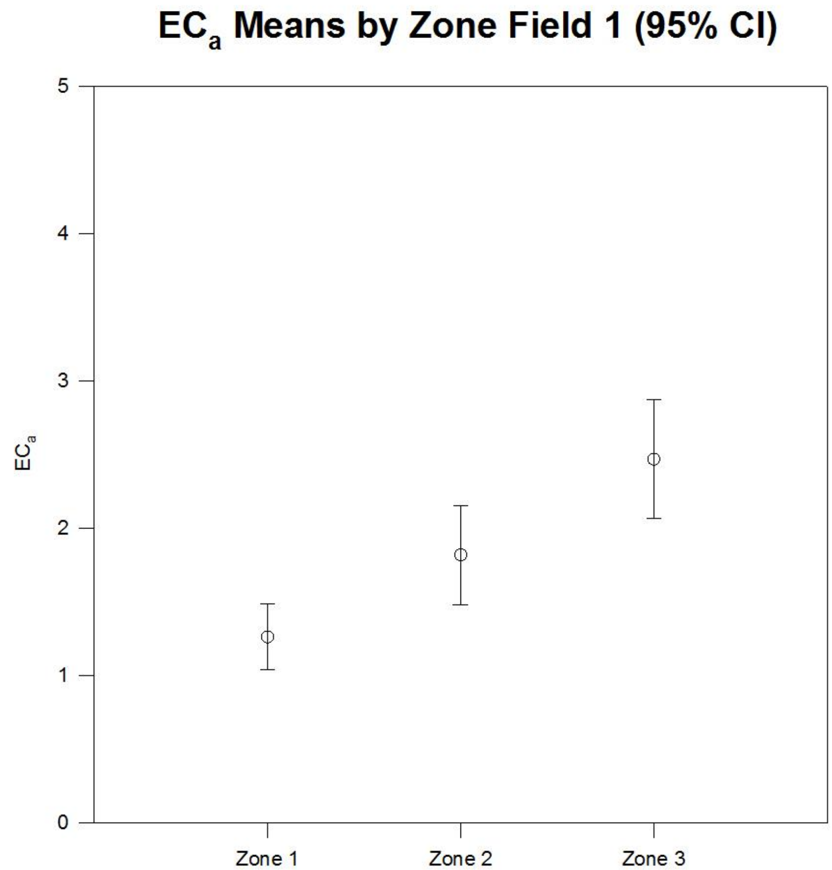

Figure 2-1. EC_a means by EC_a zones field 1, variation show using a 95% confidence interval.

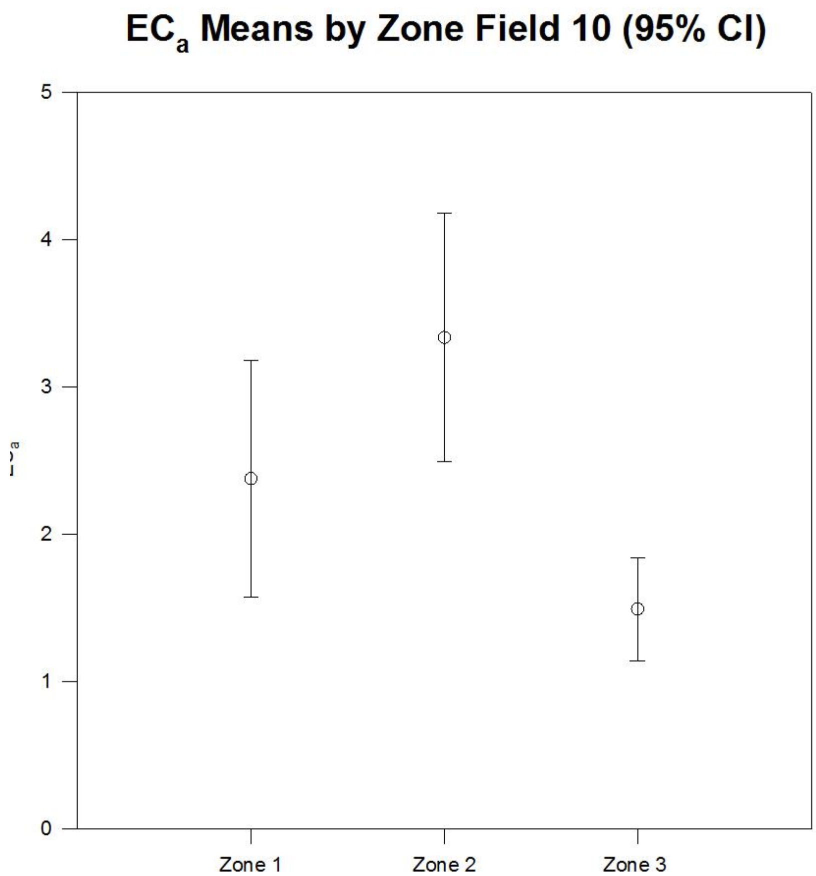

Figure 2-2. EC_a means by EC_a zones for field 10, variation shown using a 95% confidence interval.

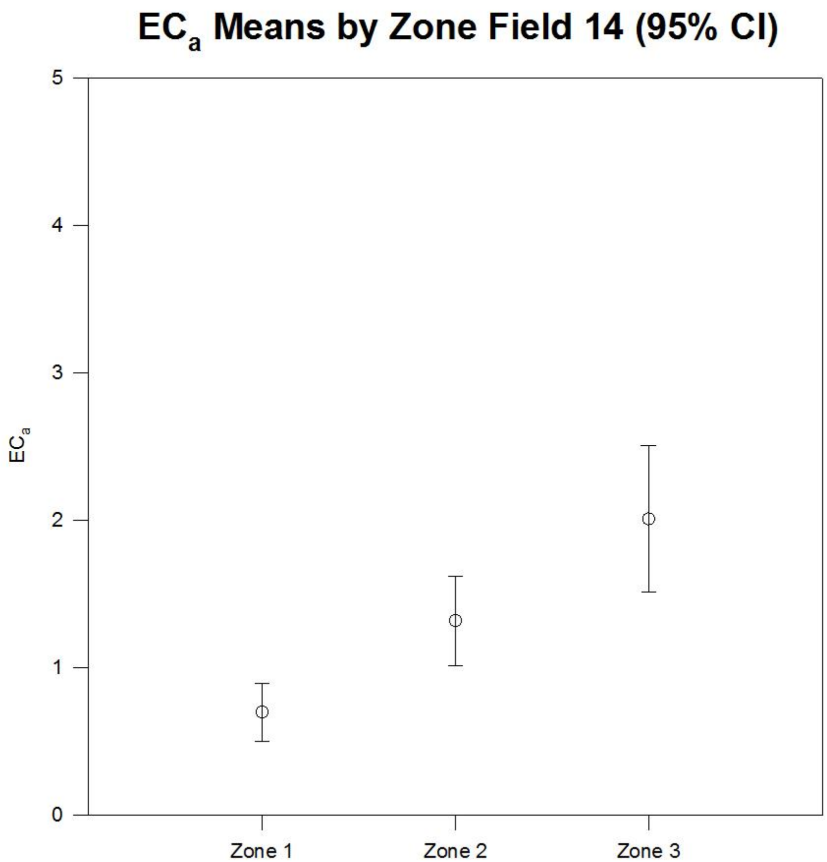

Figure 2-3. EC_a means by EC_a zones for field 14, variability shown using a 95% confidence interval.

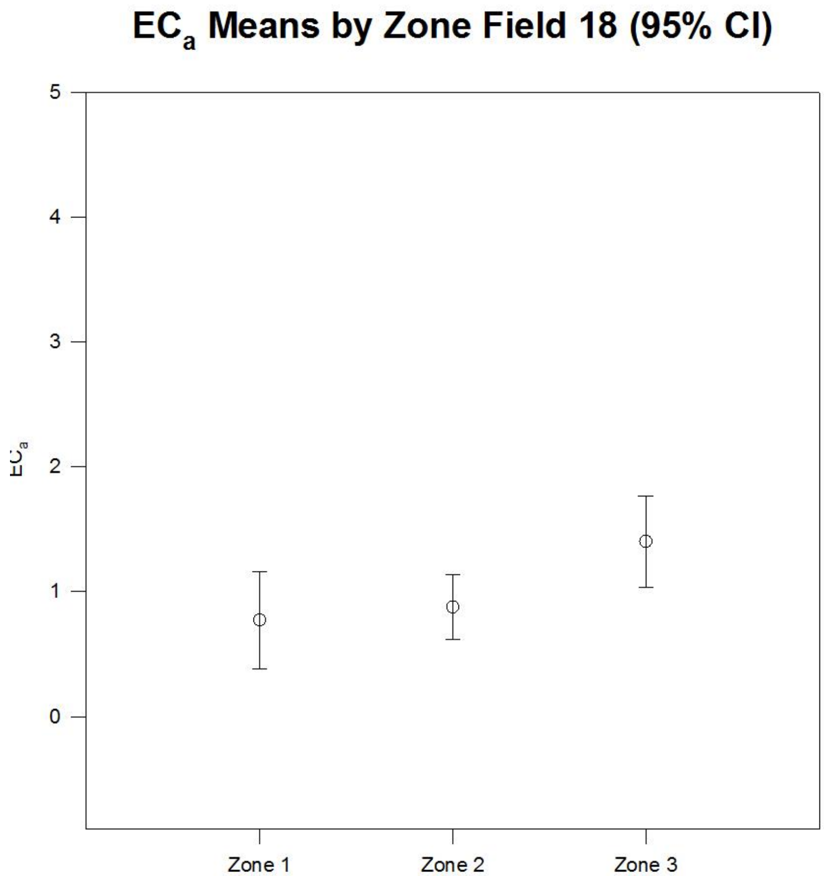

Figure 2-4. EC$_a$ means by EC$_a$ zones for field 18, variability shown using a 95% confidence interval.

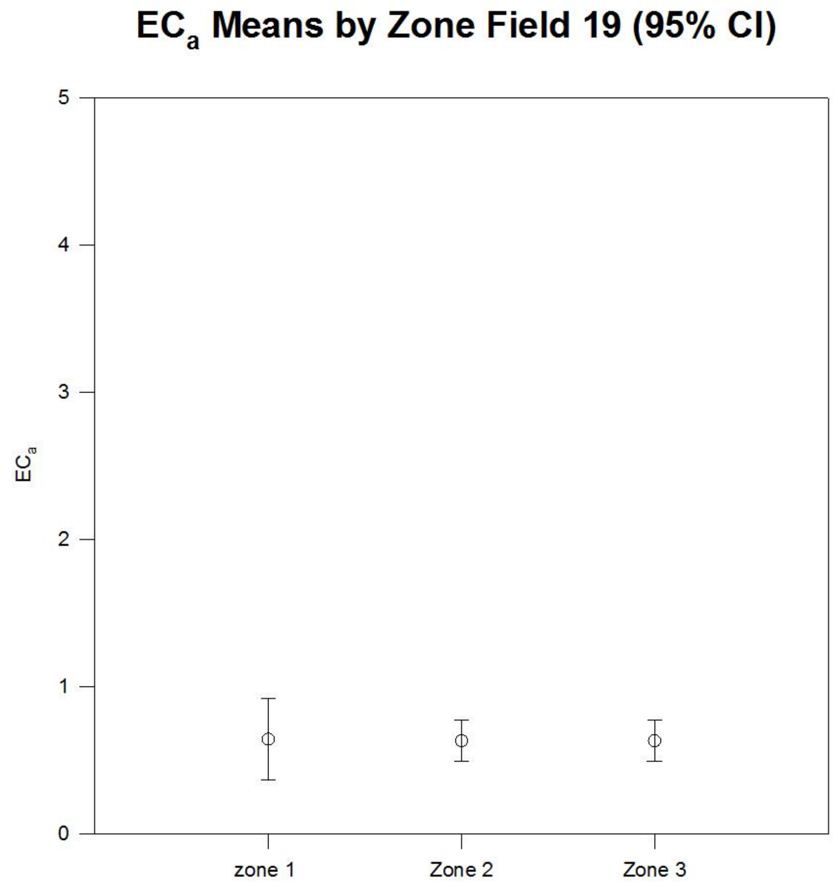

Figure 2-5. EC_a means by EC_a zones for field 19, variability shown using a 95% confidence interval.

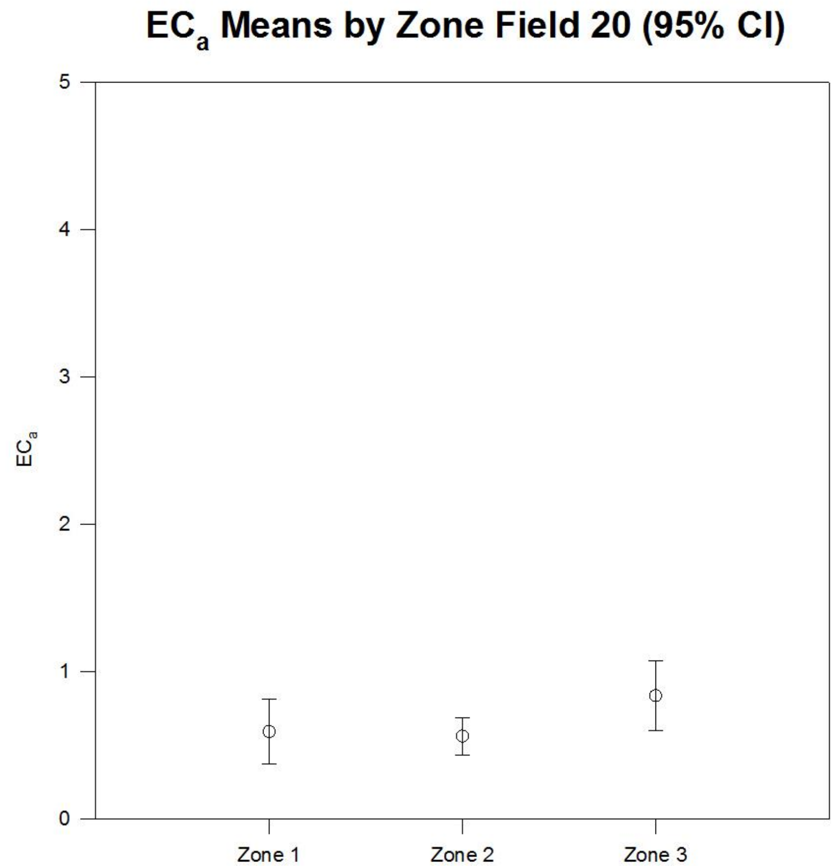

Figure 2-6. EC_a means by EC_a zones for field 20, variability shown using a 95% confidence interval.

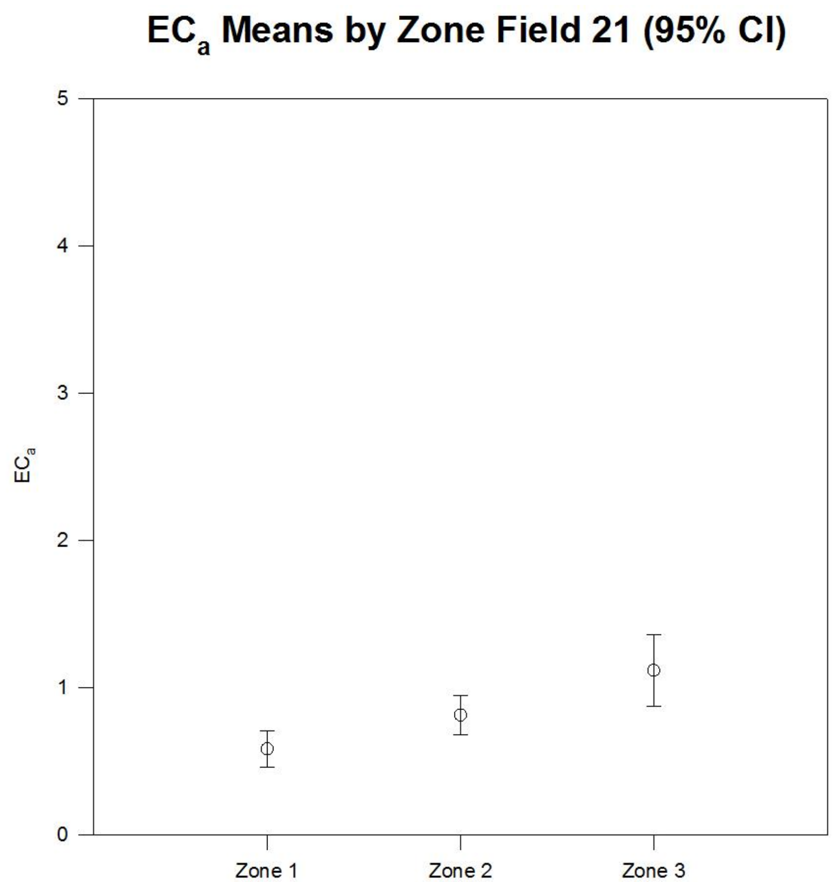

Figure 2-7. EC_a means by EC_a zones for field 21 variability shown using a 95% confidence interval.

Table 2-2. Summary of linear regression of soil properties and yield to soil EC_a and yield ($p < 0.05$).

Field	1		10		14		18		19		20		21	
Property	EC_a	Yield	EC_a	Yield	EC_a	Yield	EC_a	Yield	EC_a	Yield	EC_a	Yield	EC_a	Yield
P	0.23		0.49	0.16	0.26				0.16					
K			0.15		0.25				0.16				0.12	
Mg	0.18	0.28	0.15	0.27					0.16					
Ca			0.17	0.23										
CEC		0.22		0.25									0.13	
Yield		-	0.17	-		-		-		-		-		-
EC_a	-		-	0.17	-		-		-		-		-	
pH	0.3								0.12					
%silt				0.21									0.33	0.15
%clay				0.15					0.2				0.17	
%sand				0.21					0.25		0.11		0.28	0.13
%siltclay				0.24					0.25		0.14		0.28	0.13
%bsMg	0.34				0.18									
%bsCa			0.16		0.23									
%bsH	0.3				0.18									
%bsK			0.43	0.16	0.36		0.18		0.32					

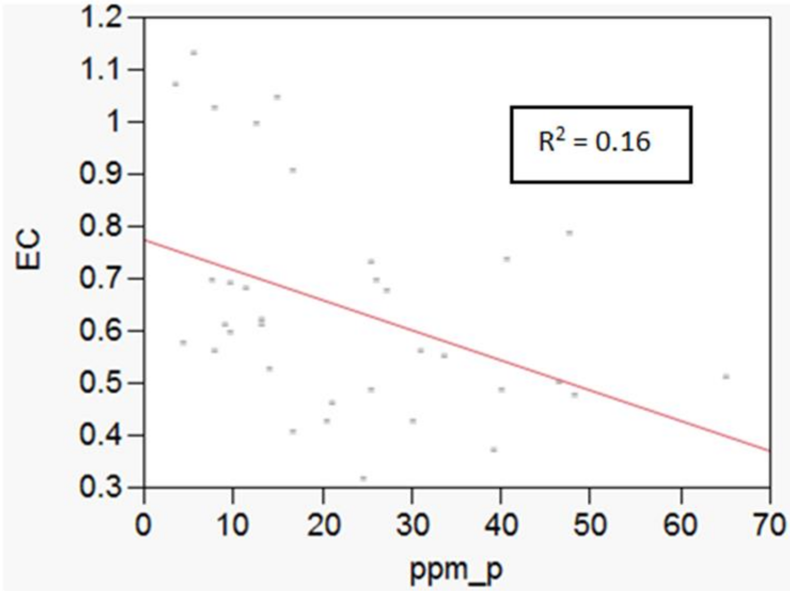

Figure 2-8. Field 19 linear regression example of soil test phosphorous and soil EC_a. $P < 0.05$.

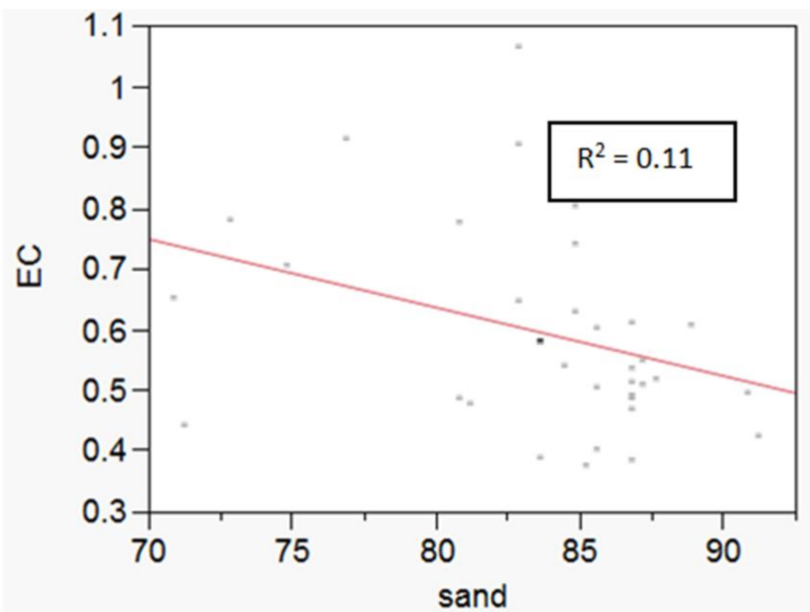

Figure 2-9. Field 20 linear regression example of percent sand and soil EC_a. $P < 0.05$.

Table 2-3. Summary of average P, K, Ca, Mg by EC_a Zone and whole field with SE by field. "a, b, c" indicating difference by zone ($p<0.01$)

	Field	mg Kg^{-1}	Zone 1	Zone 2	Zone 3	Whole Field
P	1	Average	28.25 a	20.25 b	17.00 b	24
		SE	2.36	2.28	2.9	1.79
	10	Average	26.88 a	12.36 b	18.00 ab	19.44
		SE	4.06	1.82	6.66	2.67
	14	Average	61.62 a	33.64 b	31.86 b	44.97
		SE	6.78	3.72	4.85	4.23
	21	Average	56.06 a	45.43 b	44.83 b	48
		SE	5.18	1.95	2.65	1.97
	18	Average	27.85 a	48.07 a	46.64 a	40.85
		SE	4.11	10.62	9.22	5.87
	19	Average	21.70 a	26.26 a	17.18 a	22.63
		SE	3.48	4.32	5.39	2.53
	20	Average	43.62 a	72.05 a	75.62 a	66.58
		SE	3.76	10.51	14.13	6.67
K	1	Average	50.5	55.06	51.33	52.2
		SE	2.39	2.05	5.27	1.65
	10	Average	106.83 b	114.86 a	87.19 a	104.61
		SE	6.67	10.61	7.81	5.36
	14	Average	68.23 b	105.82 a	98.00 a	88.29
		SE	8.12	6	4.01	5.12
	21	Average	57.63 a	71.00 a	69.78 a	67.19
		SE	5.78	3.81	3.37	2.68
	18	Average	38.04 a	37.46 a	27.12 a	40.857
		SE	4.31	3.47	2.82	3.195

Table 2-3. Continued

	Field	mg Kg^{-1}	Zone 1	Zone 2	Zone 3	Whole Field
P	1	Average	28.25 a	20.25 b	17.00 b	24
		SE	2.36	2.28	2.9	1.79
	10	Average	26.88 a	12.36 b	18.00 ab	19.44
		SE	4.06	1.82	6.66	2.67
	14	Average	61.62 a	33.64 b	31.86 b	44.97
		SE	6.78	3.72	4.85	4.23
	21	Average	56.06 a	45.43 b	44.83 b	48
		SE	5.18	1.95	2.65	1.97
	18	Average	27.85 a	48.07 a	46.64 a	40.85
		SE	4.11	10.62	9.22	5.87
	19	Average	21.70 a	26.26 a	17.18 a	22.63
		SE	3.48	4.32	5.39	2.53
	20	Average	43.62 a	72.05 a	75.62 a	66.58
		SE	3.76	10.51	14.13	6.67
	19	Average	38.04	37.47	27.12	35.3
		SE	4.32	3.48	2.82	2.27
	20	Average	45.25	44.75	53.188	47.03
		SE	3.31	2.66	3.96	1.82
Mg	1	Average	587.21 a	588.81 a	569.17 a	585.41
		SE	32.47	29.25	32.74	20.26
	10	Average	118.25 a	165.50 a	112.81 a	133.61
		SE	16.84	17.93	7.04	10.22
	14	Average	116.38 a	89.45 a	89.50 a	100.76
		SE	15.52	7.4	7.58	7.59
	21	Average	75.18 a	55.54 a	75.83 a	66.5
		SE	12.06	12.05	16.43	8.08
	18	Average	89.71 a	63.14 a	91.64 a	81.5
		SE	20.51	5.92	15.76	8.88

Table 2-3. Continued

	Field	mg Kg^{-1}	Zone 1	Zone 2	Zone 3	Whole Field
Mg	19	Average	77.41 a	79.26 a	83.00 a	79.48
		SE	8.87	7.4	11.04	4.92
	20	Average	68.68 a	59.66 a	69.5 a	63.97
		SE	7.44 a	5.65 a	9.60 a	3.87
Ca	1	Average	74.58 a	72.69 a	78.50 a	74.43
		SE	6.88	5.33	5.76	4.13
	10	Average	583.83 b	811.86 a	602.94 b	669.68
		SE	59.94	63.14	33.01	38.39
	14	Average	660.96 a	534.18 a	557.93 a	592.71
		SE	73.54	34.24	34.35	35.65
	21	Average	509.00 a	360.84 a	455.35 a	426.51
		SE	99.19	86.68	101.46	56.42
	18	Average	597.07 a	488.42 a	580.00 a	555.16
		SE	91.88	29.53	55.04	36.718
	19	Average	412.91 a	438.3 a	410.31 a	423
		SE	25.57	33.55	39.66	18.72
	20	Average	434.75 a	461.91 a	570.43 a	482.26
		SE	39.13	24.53	65.14	21.92
EC_a	1	Average	1.26 a	1.82 b	2.47 c	1.45
		SE	0.01	0.03	0.08	0.02
	10	Average	1.49 a	2.38 b	1.49 c	2.52
		SE	0.04	0.06	0.03	0.05
	14	Average	0.69 a	1.32 b	2.01 c	1.2
		SE	0.01	0.01	0.03	0.02
	21	Average	0.58 a	0.81 b	1.12 c	0.83
		SE	0.01	0.01	0.02	0.01
	18	Average	0.51 a	0.88 b	1.4 c	0.77
		SE	0.01	0.01	0.03	0.01

Table 2-3. Continued

	Field	mg Kg^{-1}	Zone 1	Zone 2	Zone 3	Whole Field
EC_a	19	Average	0.44 a	0.63 b	0.98 c	0.64
		SE	0	0	0.02	0.01
	20	Average	0.41 a	0.56 b	0.84 c	0.59
		SE	0.01	0	0.01	0.01

Table 2-4. Average yield (kg/ha) for all study fields, separated by zone and summarized by whole field mean for each.

Yield (kg/ha)					
Field		Zone 1	Zone 2	Zone 3	Whole Field
1	Average Yield	2571	2646	2447	2586
	SE	113	75	111	71
10	Average Yield	4271	4040	4490	4229
	SE	133	85	191	81
14	Average Yield	4326	4539	4393	4434
	SE	168	187	175	107
21	Average Yield	4265	3947	3764	3976
	SE	175	225	290	143
18	Average Yield	6129	5681	6413	6064
	SE	687	467	437	240
19	Average Yield	7479	6242	6862	6757
	SE	155	190	489	177
20	Average Yield	5830	6833	5926	6231
	SE	255	368	282	222

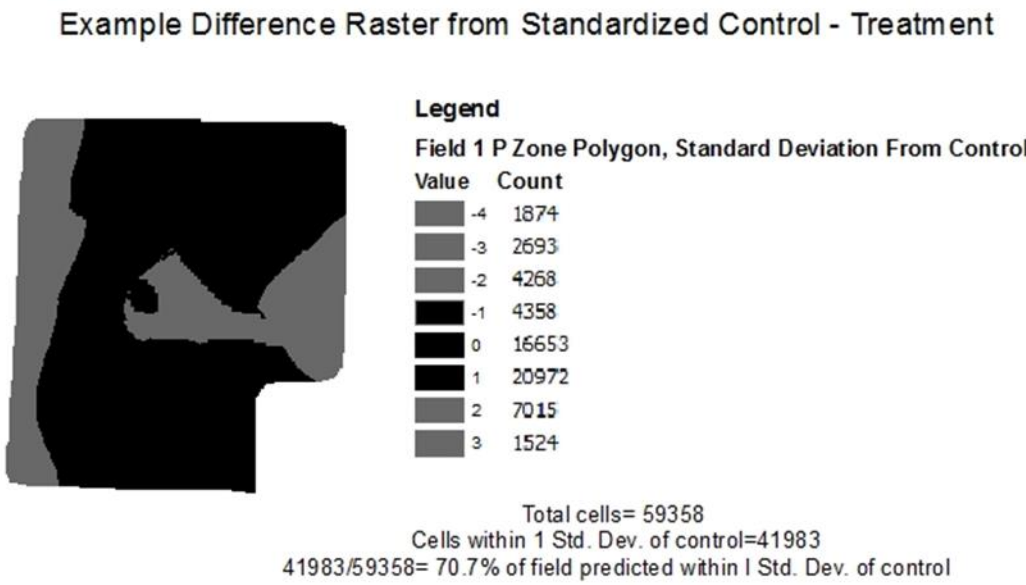

Figure 2-10. Example of a final difference raster from the standardized control minus treatment method for comparing our four sample schemes

Table 2-5. The percent (%) of field area predicted within 1 standard deviation of the control by field and nutrient. Mehlich 1 extractable phosphorus (P), potassium (K), calcium (Ca), and magnesium (Mg). Grid no interpolation (GNI), grid with interpolation (GWI), zone polygon (ZP) and zone interpolated all.

Nutrient	Treatment	Field 1	Field 10	Field 14	Field 21	Field 18	Field 19	Field 20	Mean
P	GNI	85	100	99	96	90	96	100	95
	GWI	95	100	99	95	80	95	100	94
	ZIA	90	90	97	98	92	100	100	95
	ZP	90	100	96	99	71	88	100	92
K	GNI	91	94	84	100	100	100	91	94
	GWI	96	98	99	97	100	100	88	96
	ZIA	88	78	96	96	100	100	90	92
	ZP	88	91	97	100	80	90	93	91
Ca	GNI	64	97	94	64	93	86	99	85
	GWI	100	99	94	100	87	86	99	95
	ZIA	85	96	93	85	88	100	96	91
	ZP	88	38	94	88	86	95	91	83
Mg	GNI	65	96	97	94	86	85	84	87
	GWI	76	99	98	89	98	88	100	93
	ZIA	63	94	99	91	100	100	99	92
	ZP	99	81	95	94	87	90	93	91

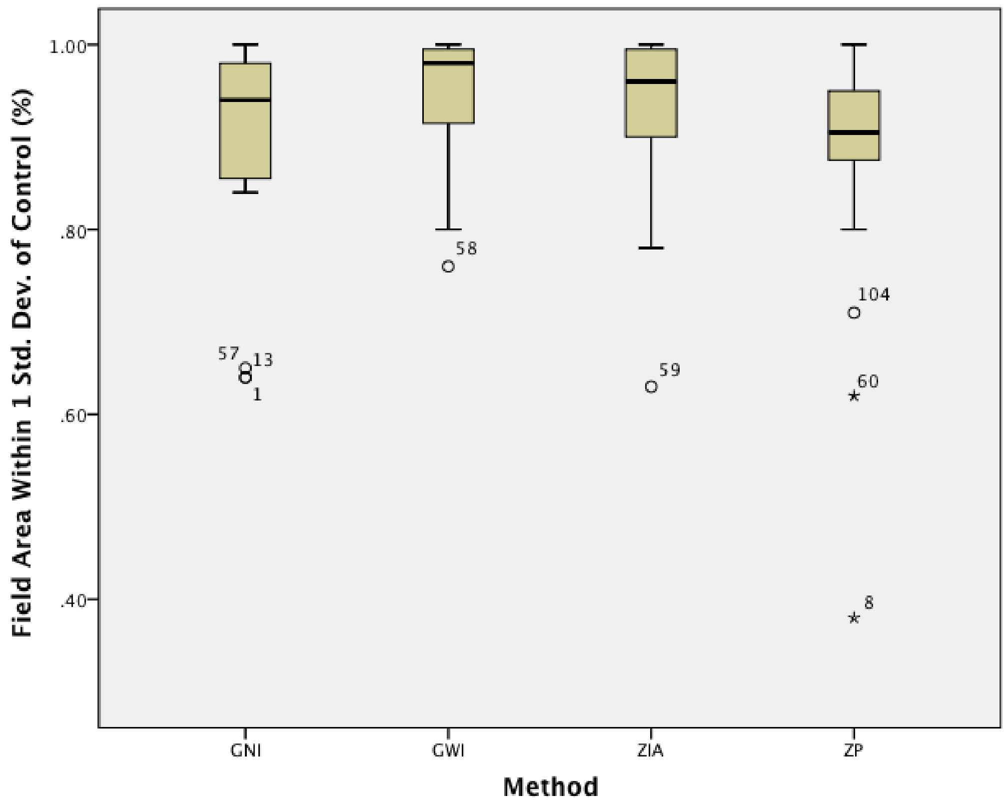

Figure 2-11. Average field area predicted within one standard deviation of the control (%) by our four treatment methods, GNI, GWI, ZIA and ZP.

Table 2-6. Results from the subsample least squares mean comparisons. Treatment occurrence in table indicates it was similar to the control dataset (p<0.05).

Field	1	10	14	21	18	19	20
Phosphorous	ZIA	ZP	GWI		ZP	ZP	
Potassium					ZIA	ZP	
Calcium	ZIA, GWI				ZIA	ZP, GNI	
Magnesium	GWI				GNI, GWI		

Table 2-7. Average value from 10 x 10 meter subsample procedure. Average is provided by treatment for P, K, Mg, Ca.

Field	Treatment	P	K	Mg	Ca
1	GNI	25	53	71	592
	GWI	25	51	75	576
	ZIA	26	59	70	559
	ZP	30	59	68	594
	Control	26	49	72	582
	Mean	26	54	71	586
10	GNI	27	110	150	725
	GWI	22	107	158	748
	ZIA	8	85	109	547
	ZP	16	92	96	482
	Control	16	98	139	104
	Mean	18	98	130	521
14	GNI	47	572	116	572
	GWI	46	658	113	658
	ZIA	53	578	97	578

Table 2-7. Continued

Field	Treatment	P	K	Mg	Ca
14	ZP	56	576	99	576
	Control	46	604	108	604
	Mean	50	87	107	598
21	GNI	50	69	172	588
	GWI	46	69	85	556
	ZIA	47	62	92	631
	ZP	49	68	98	597
	Control	47	47	56	380
	Mean	48	67	106	550
18	GNI	26	54	73	500
	GWI	25	54	79	497
	ZIA	42	50	74	566
	ZP	38	54	76	368
	Control	39	49	82	549
	Mean	34	52	76	496
19	GNI	21	34	34	410
	GWI	20	36	77	420
	ZIA	24	36	79	423
	ZP	23	36	75	417
	Control	23	36	69	413

Table 2-7. Continued

Field	Treatment	P	K	Mg	Ca
19	Mean	22	36	69	417
20	GNI	83	52	67	511
	GWI	66	52	66	510
	ZIA	56	43	62	466
	ZP	54	54	52	254
	Control	67	67	63	478
	Mean	69	50	63	444

CHAPTER 3
DISCUSSION AND CONCLUSION

Discussion

Analysis of soil revealed variation of soil nutrient content, CEC, and texture within and among fields. This suggests that site-specific assessment of soil and application of nutrients could be beneficial for the soils evaluated in the study. Moreover, fields with soil nutrient content below critical values for peanut production provides an opportunity to observed spatial differences in yield response.

Measurement of EC_a and delineation of zones that are agronomically significant is essential for site-specific management of nutrients. The methods employed to delineate zones according to EC_a values did separate fields into three statistically distinct zones. Yet, the agronomic significance was uncertain. EC_a values measured in the seven fields were lower than values reported for other soil types. Examples include ECa ranges of 4.2 to 22.7 mS m^{-1} and 7.3 to 40.2 mS m^{-1} in two Missouri fields with claypan (Kitchen et al., 2005). Mollisol soils studied in Iowa by Brevik et al (2006) contained EC_a ranges of 20 to 70 mS m-1. At study sights in Colorado, within semi-arid great plains containing Platner and Rago loam soils, Johnson et al. (2001) found EC_a ranges between 0 and 78 mS m-1. Factors influencing ECa values can differ among soil types and environments. In our Northwest Florida study area with soil types being predominately Red Bay, Lucy and Dothan sandy loams or Fuquay loamy sand, EC_a values ranged between 0.59 and 2.48 mS m-1.

Williams and Baker (1982) found that in non-saline soils, bulk soil conductivity variability is mostly attributed to soil moisture, texture, and CEC. Variability of these factors are influenced by a combination of soil physical and chemical properties, including but not limited to; bulk density, clay mineralogy and content, organic matter, and soil temperature (Corwin and Lesch, 2005; Rysan and Sarec, 2008). In general, sands have low bulk soil conductivity and will lower measured values of EC_a. Silts have medium bulk soil conductivity and clays have higher bulk soil conductivity (Lund et al., 1999). Because of within field variability of soil properties, correlation between EC_a and specific soil properties may vary from field to field (Corwin and Lesch, 2003). Regarding EC_a relationships to soil nutrients, Johnson et al (2003) found P to be negatively correlated with EC_a, and clay content to be positively correlated with EC_a in Platner, Weld, and Rago loam soils located in northwest Colorado. Our regression analysis determined soil nutrients in soil did not provide consistent relationships to EC_a. In addition, texture and CEC variation were not influencing our EC_a measurements. Therefore, soil moisture or variations in surface cover of the soil may have influenced EC_a variation in our fields.

In comparison of soil nutrient means by zone, four of seven fields had soil nutrient values that were different by zone ($p<0.05$), however in every case the difference was between only two of the three zones. Other studies have found significant relationship between soil nutrients and EC_a delineated zones, including Johnson et al. (2003) in which extractable P was related to EC_a zones ($p<0.10$). Their study area was located in northwestern Colorado, with Platner, Weld, and Rago loam soils. Fleming et al. (2004) examined the relationship between soil P and K between EC_a delineated zones in two field in northeastern Colorado, finding relationships between K in two of three zones in one field, and in all three zones in their other study field ($p<0.05$). No difference was found between P in field one, and differences in two of three zones was found in field two ($p<0.05$). Our nutrients by zone results are similar to that of Fleming et al. (2004), in that we identified relationships between nutrients by two of our three EC_a zones.

In the current project, the number of zones was predetermined to reflect the sampling design commonly practiced in the region. Other reports have used from three and up to eight zones. However, three zones did not delineate three areas within the field that had significantly different levels of soil test nutrients or nutrient requirement. Furthermore, no difference in yield was detected across the three zones in any field. This suggests three zones may not have been appropriate for the fields evaluated in our study. The use of a software program, like Management Zone Analyst (MZA), would be helpful in selecting the optimal number of zones for your respective dataset (Fridgen et al., 2004).

Results from the subtraction of standardized control raster's from standardized treatment raster's found no difference ($p > 0.10$) among methods when comparing treatment to control maps for individual nutrients. Standardization of P, K, Ca, and Mg levels for each field allows observations of all nutrients to be pooled for comparison of sampling methods, generating our conclusion that grid with interpolation and zone with interpolation sampling schemes resulted in greater ($p < 0.10$) field area within 1 standard deviation of the control map compared the zone-polygon scheme. Fleming et al. (2004) evaluated an EC_a delineated zone sampling scheme in two study fields by first standardizing collected field EC_a data to a mean of zero and standard deviation of one, and thereafter creating three management zones in both study fields and sampling on a 76 meter grid. Samples were measuring for soil variables including P and K.

Relationships between zones and soil variables were evaluated using ANOVA ($p<0.05$), finding relationships between zones and soil variables including P in one of two fields, in two of three zones. K was related to zones in both fields, in two of three zones and in all three zones ($p<0.05$). Fleming et al. (2004) compared their EC_a zone relationships to soil variables to the relationship between zones created by soil color, and found that EC_a delineated zones to be more effective at identifying homogeneous in-field management zones. Fleming et al. (2004) compared 76 meter grid sampling to EC_a delineated zone sampling. ANOVA was used to determine relationship between grid and zone soil variables and logistic regression was used to examine how well the zone sample characterization of the soil within each EC_a zone predicted the grid sample data in each EC_a zone. Performance of the zone was evaluated by the percent of grid samples accurately predicted by the zone sample characterization. Fleming et al., (2004) found varying differences between grid and zone delineated soil samples by field. 82 to 83% of the grid samples not in the defined 10 meter transition border zone were accurately predicted by EC_a zones. Fleming et al. (2004) concluded that, “zone-based soil sampling could provide agronomically useful soil information as compared to grid soil sampling, without having the need to acquire a large number of soil samples as is the case of grid soil sampling which is time consuming, labor intensive, and cost prohibitive for most farmers.”

Conclusion

Corwin & Lesch (2005) note that EC_a measurements are complex in the sense of what soil properties are influencing their values, and whether the influencing properties are associated to field subareas that may be managed differently for production improvement. Implementation of a fertility program using EC_a delineated zones that are not related to agronomically relevant soil factors may result in improper fertilization and misallocation of resources. From our results we conclude that while EC_a variation existed within our fields, this variation was not related to useful fertility management zones. In other words, the variation in EC_a for the fields in our study had no relation to soil factors of agronomic importance. Additionally analysis of treatment methods found the grid with interpolation method to perform the same as the zone with interpolation method ($p<0.05$). From our results we conclude that while EC_a zone soil sampling for productivity management has proved appropriate in other locations with different landscapes and soil type, (Johnson et al., 2001; Kaffka et al., 2005; Kitchen et al., 2005., Sudduth et al., 2005.) zone soil sampling using EC_a measurements is not an improvement upon the traditional one hectare grid soil sampling in Northwest Florida.

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BIOGRAPHICAL SKETCH

Ashley Mason is from Canton, Illinois. Her relevant work experience includes two years employment with a soil testing and consultation company in Illinois. She received her bachelor's in agriculture education with a minor in political science Western Illinois University. At Western Illinois University Ashley was active in the National FFA. Part of Ashley's program at the University of Florida was spent at the West Florida Research and Education Center. Her degree program at the University of Florida consisted of a Master of Science in agronomy and an interdisciplinary concentration in geographic information systems.