Use of apparent soil electrical conductivity to improve sugarcane nutrient management in Florida

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Abstract

Precision agriculture is considered to be one of the most promising approaches for sustainable farming, but it requires efficient methods for accurately measuring within-field variations in soil physical and chemical properties. Apparent soil electrical conductivity (ECa) is a quick indirect measurement of soil EC with a sensor (e.g. EM-38), and the latter is used to determine spatial variations of this parameter in the field without extensive soil sampling. Correlation of ECa values with different soil nutrients in organic and mineral soils in southern Florida can help in determining its potential use to improve nutrient management in sugarcane. Data on ECa and different soil variables were collected from several 5-15 ha fallow sugarcane fields in Palm Beach (organic soil, Histosols) and Hendry (mineral soil, Entisols) counties of Florida in 2014 and 2015. Soil samples were analyzed for pH, P, Ca, Mg, S and Si in soil testing lab at the Everglades Research and Education Centre, Belle Glade. In organic soils, the bulked soil data showed significant correlations between ECa and each of soil pH (r=0.72), Mg (r=0.62), Si (r=0.52) and Ca (r=0.35). In mineral soils, there were significant correlations between ECa and each of pH (r=0.75), Pterholch-3 (r=0.73), Ca (r=0.58), and Si (r=0.46). Grouping the fields into different zones based on their location changed the correlations for the tested variables. PC-stepwise regression analysis indicated that soil pH was the major contributor to the variability in soil ECa in both soil types. Results showed that the correlations between ECa and the measured soil parameters were not consistent through all the tested zones or the fields. Therefore, ECa may be more precisely used in management of these parameters at zonal or field level. In bulk soil, the correlations between ECa and soil pH were highest in both soils and that supports the need of further exploration of ECa maps in soil pH management across a wide range of sugarcane fields in Florida. Alternatively, ECa may be used in conjunction with soil sampling to determine the spatial variability of the soil variables and thereafter be used for precise management of different nutrients. Further research is needed to determine the relationship between ECa and sugarcane yield, and for the use of yield maps in ECa map calibrations.

Key words precision agriculture, soil EC, soil variables, Pearson correlation, soil pH

INTRODUCTION

For sustainable sugarcane (Saccharum spp. hybrids) cultivation, it is important to maintain the balance between maximizing sugarcane productivity and economic stability while minimizing the utilization of finite natural resources and any detrimental environmental impacts of associated agrichemical pollutants and/or in-field practices. Precision agriculture (PA) is considered to be one of the most promising approaches for attaining sustainable agriculture. Apart from the need for accurate and precise measurement of in-field yield variation, it is important to have access to efficient methods for accurately determining in-field variations in soil physical and chemical properties (Bullock and Bullock 2000). Site-specific nutrient management can improve crop yield and also reduce fertilizer use in some cases (Bongiovanni and Lowenberg-Deboer 1999). Traditionally, site-specific nutrient management depends on intensive soil sampling, but unfortunately the cost associated with soil sampling and soil testing is often higher than economic returns (English et al. 1999).

The measurement of apparent electrical conductivity (ECa) is a technology that has become invaluable for identifying soil physicochemical properties that could be influencing crop yield patterns and for establishing the spatial variation of these soil properties (Corwin and Lesch 2003). By definition, electrical conductivity (EC) is the ability of a material to conduct (transmit) an electrical current and it is commonly expressed in units of milliSiemens per meter (mS/m). Apparent soil EC (ECa) is an indirect measurement of soil EC, which can be measured quickly with electromagnetic induction equipment such as an EM-38 instrument. Measurement of spatial variation in ECa is being widely used for several applications in PA. For example, measurement of soil ECa has been successfully used to determine soil salinity, clay content, soil water content, and available nitrogen (N) and phosphorus (P) (Kachanoski et al. 1988; Williams and Hoey 1987; Rhoades et al. 1976; Freeland 1989; Eigenberg et al. 2002; Motavalli et al. 2013). Soil salinity is considered to be one of the major factors effecting soil ECa (Malicki and Walczak 1999). In non-saline soils, ECa may change with changes in the type and number of cations (e.g. calcium (Ca2+), magnesium (Mg2+) and potassium (K+) commonly associated with exchange sites on the
soil particles. Kitchen et al. (1999) reported the potential use of $EC_a$ in identifying management zones with different productivity and nutrient requirements.

The above studies suggested that $EC_a$ mapping could be successfully applied in different parts of the world and its use needed to be explored for southern Florida. Sugarcane is the major agricultural crop in southern Florida around Lake Okeechobee and nutrient management is a key for profitable and sustainable sugarcane production. Conventional farming treats a field uniformly and ignores the natural inherent variability of soil and crop conditions between and within fields. Progressive growers use soil sampling as a common method to determine spatial variation within their fields. However, soil sampling is a very labor intensive and expensive method. In addition, inadequate number of soil samples may not accurately represent variability within the field. This problem can be solved through soil $EC_a$ mapping, which can help in guided soil sampling or directly in precision nutrient management. Co-kriging of $EC_a$ can also be used to reduce the number of soil samples without sacrificing the accuracy of soil maps. The usefulness of $EC_a$ mapping depends on the relationship between $EC_a$ and soil variables of agronomic importance. Therefore, the objectives of our study were to evaluate the use of soil $EC_a$ mapping as a management tool in organic and mineral soils of southern Florida.

**MATERIALS AND METHODS**

**Field measurements and soil sampling**

The research was conducted in several sugarcane fields on organic and mineral soils in Palm Beach and Hendry counties of Florida, USA. The organic soils are Histosols (euic, hyperthermic lithic haplosaprist) and mineral soils are Entisols (siliceous, hyperthermic mollic psammaquents). The correlation between soil $EC_a$ and different soil variables including soil depth (from surface to bedrock), soil moisture, pH, P, K, Ca, Mg, and silicon (Si) was determined by collecting data from eight fields with a total area of 72 ha on organic soil and six fields with a total area of 25 ha on mineral soil in southern Florida. These fields were farmed as commercial sugarcane production systems. Soil $EC_a$ and other variables were measured just before sugarcane planting when the fields were thoroughly cultivated and leveled. The size of each field was 5-15 ha. Each field was divided into 40 x 100 m grids to enable collection of soil samples and $EC_a$ data.

$EC_a$ was measured with an EM-38 sensor (Geonics Limited, Mississauga, Ontario, Canada) and georeferenced with a Trimble GPS receiver. The data were recorded with an Archer field computer attached to the EM-38 and the GPS receiver. The EM-38 works on the principle of electromagnetic induction and produces an electromagnetic field in the soil. There are two transmitting coils and two receiving coils in an EM-38 instrument that are separated by 0.5 m or 1 m. The transmitting coil transmits electrical current and the receiver coil receives it back. The strength of this electrical current is determined by the soil $EC_a$ values. The separation between the transmitting and receiving coil determines the depth of data collection, which is either 0.75 m (0.5 m separation) or 1.5 m (1.0 m separation) in vertical method. We used both depths in some fields to determine the relationship between them, and only 1.5 m in the other fields.

Soil cores were collected to a depth of 15 cm from the similar points in each grid. Soil depth was measured by probing and soil moisture was measured using the gravimetric method in the organic soils and with a Field Scout digital moisture sensor in the mineral soils. The pH, P, K, Ca, Mg and Si values were determined in the soil testing laboratory at the Everglades Research and Education Center (EREC), Belle Glade.

**Soil analysis procedure**

Each soil sample was mixed thoroughly, placed in aluminum drying pans, air-dried in a forced-air drying room at 31°C, and sieved through a 2-mm screen before analysis. Soil pH$_{\text{water}}$ was determined for all samples (15 cm$^3$ soil/30 mL water). Mehlich 3 extractant (0.2 M CH$_3$COOH, 0.25 M NH$_4$NO$_3$, 0.015 M NH$_4$F, 0.013 M HNO$_3$, and 0.001 M EDTA) was used to extract the soil (2.5 cm$^3$ soil/25 mL extractant ratio) with a 5-minute shaking time immediately after adding the extractant to the soil samples. The samples were filtered prior to analysis. Phosphorus concentrations were determined with a discrete analyzer (Seal AQ2) for Mehlich 3-extractable P. Potassium, Ca, Mg, and Si were extracted with 0.5 M acetic acid using a 10 cm$^3$ soil/25 mL extractant ratio. Soil samples were allowed to stand overnight and then were shaken for 50 minutes before filtering for analysis. Concentrations of K, Ca, Mg, and Si were determined with inductively coupled argon plasma spectroscopy (Perkin-Elmer Optima 5300).
Statistical analysis

The PROC CORR procedure in SAS (SAS 2014) was used to perform correlation analyses for each location and each soil type. Stepwise regression analyses were then performed to identify the contribution of the various soil test variables affecting soil ECₐ in each soil type. This was done using the PROC REG, SELECTION = STEPWISE procedures in SAS. In stepwise regression analyses, the independent variables are entered one by one to the regression equation to improve the \( R^2 \) values until the additional variables stop making significant contributions in the regression equation.

RESULTS AND DISCUSSION

Data analysis from the tested fields showed significant positive correlation \( (r=0.94) \) between soil ECₐ measurements at greater depth (ECdeep) and ECₐ measurements at shallow depth (ECshallow). Therefore, we used only ECdeep to determine the correlations of ECₐ with tested soil variables in this study. In the bulk data for each soil type, the Pearson correlation coefficient was significant \( (r>0.18 \text{ at } P<0.05) \) between ECₐ and soil pH \( (r=0.72) \), Mg \( (r=0.62) \), Si \( (r=0.52) \) and Ca \( (r=0.35) \) in organic soil (Fig. 1). In mineral soil, the correlations were significant between EC and pH \( (r=0.75) \), \( P_{\text{Mehlich-3}} \) \( (r=0.73) \), Ca \( (r=0.58) \), and Si \( (r=0.46) \) (Fig. 2). The other tested correlations were weak and/or insignificant. Our results show that soil pH had the strongest correlation with ECₐ in both soil types, and Ca and Si were also common contributors to ECₐ variations in both soil types.

Fig. 1. Significant correlations between soil ECₐ and specific variables in bulk data for organic soil.
The tested fields were then grouped into three zones based on their location (EREC, Main Farm, and Hillsboro Farm) for organic soils and two zones (PPI and Hilliards) for mineral soils. The correlations between EC$_a$ and other variables in each zone are listed in Table 1.

**Table 1.** Pearson correlation coefficient ($r$) for the relationship between EC$_a$ and other variables in different zones of organic and mineral soils in southern Florida.

<table>
<thead>
<tr>
<th>Soil</th>
<th>Zone</th>
<th>pH</th>
<th>P</th>
<th>K</th>
<th>Ca</th>
<th>Mg</th>
<th>Si</th>
<th>Depth</th>
<th>Moisture</th>
</tr>
</thead>
<tbody>
<tr>
<td>Organic</td>
<td>EREC (n=46)</td>
<td>0.69**</td>
<td>-0.48**</td>
<td>0.03</td>
<td>0.28</td>
<td>0.74**</td>
<td>0.38</td>
<td>0.57**</td>
<td>-0.10</td>
</tr>
<tr>
<td></td>
<td>Main Farm (n=108)</td>
<td>0.84**</td>
<td>-0.58**</td>
<td>0.43**</td>
<td>0.36**</td>
<td>0.55**</td>
<td>0.48**</td>
<td>0.02</td>
<td>-0.34**</td>
</tr>
<tr>
<td></td>
<td>Hillsboro Farm (n=23)</td>
<td>0.51**</td>
<td>0.25</td>
<td>0.01</td>
<td>-0.28</td>
<td>-0.19</td>
<td>0.21</td>
<td>0.78**</td>
<td>--</td>
</tr>
<tr>
<td>Mineral</td>
<td>PPI (n=22)</td>
<td>0.46*</td>
<td>0.64**</td>
<td>0.02</td>
<td>0.34</td>
<td>0.45*</td>
<td>--</td>
<td>--</td>
<td>--</td>
</tr>
<tr>
<td></td>
<td>Hilliards (n=40)</td>
<td>0.54**</td>
<td>0.02</td>
<td>0.13</td>
<td>0.49**</td>
<td>0.56**</td>
<td>0.46*</td>
<td>--</td>
<td>--</td>
</tr>
</tbody>
</table>

Soil depth and moisture were measured only in organic soil; * and** indicate significant differences at $p < 0.05$, and 0.01, respectively; -- indicates missing data.

The relationship of soil pH with EC$_a$ was significant among all the zones for both soils. For organic soils, P showed significant negative correlation with EC$_a$ at EREC ($r=-0.48$) and Main Farm ($r=-0.58$). Potassium, Ca, and Si showed significant positive correlation with EC$_a$ at Main Farm only. Magnesium had significant positive correlation with EC$_a$ at both EREC and Main Farm. Soil depth showed significant positive correlations with EC$_a$ at EREC ($r=0.57$) and Hillsboro Farm ($r=0.78$). Soil depth had the greatest correlation with EC$_a$ at Hillsboro Farm. This may have masked the effect of Ca, Mg
and Si as their relationship with ECₐ was insignificant in this zone. Soil moisture showed unexpected negative correlation with ECₐ at Main Farm, but the correlations were weak and may not have any practical applications in soil moisture management. These negative correlations may have resulted from the masked effect of other variables on ECₐ in these fields. Sudduth et al. (2005) reported a similar negative correlation of ECₐ with soil moisture in some loamy soil fields in Wisconsin. Phosphorus had significantly positive correlation at PPI (r=0.64) and no correlation at Hilliards for mineral soils. Positive correlation of P with ECₐ in mineral soils and negative correlation in organic soil may be the result of interactions with other soil parameters. For example, the soil depth in organic soils was <1.5 m in most of the tested fields, but it was >1.5 m in mineral soils. As EM-38 measures ECₐ up to 1.5 m soil depth, the effect of variable soil depth in organic soils may be one of the factors causing different relationships of soil ECₐ with P in organic versus mineral soils. Higher organic matter in organic soil than mineral soil is the other possible reasons for different correlations of ECₐ with P in the two soil types. Sudduth et al. (2005) reported strong correlations between ECₐ and some soil parameters (silt, sand, organic C, soil moisture and paste EC) in some study fields and not in others. In addition, the correlations between ECₐ with silt were negative in some soils (Missouri, Illinois and Wisconsin) and positive in others (Michigan, South Dakota and Iowa). It suggests that the relationship between ECₐ and the measured soil parameters may vary in different soil types or even in different fields of same soil type. Calcium and Si had significant correlations with ECₐ at Hilliards only, and Mg was significant at both PPI and Hilliards.

The correlation of bulk ECₐ with different soil variables has been determined in several studies, including salinity (Hendrickx et al. 1992; McKenzie et al. 1997), soil Ca and Mg (McBride et al. 1990), soil water content (Sheets and Hendrickx 1995), and depth to clay pan (Doolittle et al. 1994). Literature also shows variable results for bulked soil data compared to individual fields. Mueller et al. (2003) reported a relatively good correlation between ECₐ and clay content (r=-0.40) for bulked soil data across three locations. The time specific correlations in individual fields were better with positive correlations of ECₐ with clay, moisture content, Ca, and Mg; and negative correlations of ECₐ with depth to bedrock. Heiniger et al. (2003) reported overall weak and negative relationship between ECₐ and P, but the relationship was significant and positive for individual soil series. They also reported that the strong positive relationship between ECₐ and CEC was primarily due to changes in Ca and Mg concentrations with changes in CEC. We have a similar situation in our study as a strong positive correlation between ECₐ and soil pH came with a significant correlation of ECₐ with Ca and Mg in organic soil and Ca in mineral soil. Therefore, the concentration of these cations may have an effect on soil pH and ultimately on soil ECₐ. Significant correlations of EC with soil Ca and Mg were also reported by McBride et al. (1990) and Mueller et al. (2003). In long-term poultry-amended pasture land in Missouri, Motavalli et al. (2013) reported significant positive correlations of soil ECₐ measured with EM-38 sensor and soluble, soil test Bray-1 and total P at 0-5 and 5-15 cm.

The stepwise regression analysis showed that soil pH was the major contributor to soil EC variability for both soils with regression coefficients (R²) of 0.52 and 0.56 in the organic and mineral soils, respectively (Table 2). This indicates that soil pH alone contributes to 52% and 56% variability in ECₐ in the organic and mineral soils respectively. The addition of P as a second variable in the equation increased the contribution to ECₐ variability by 11 and 13% in organic and mineral soils, respectively. In the third step, Mg and K were added in the equations to improve R² values for the organic and mineral soils, respectively. Therefore, the three variables (pH, P and Mg in organic soils and pH, P and K in mineral soils) accounted for 71% variability in the organic soil, and 72% variability in the mineral soil. Further addition of soil depth in a fourth step and Ca at in a fifth step did improve the R² value for the organic soils. No further additions were tested for the mineral soils.

**Table 2.** Stepwise regression analysis of ECₐ and other variables in bulk data from organic and mineral soils in southern Florida.

<table>
<thead>
<tr>
<th>Soil</th>
<th>Step</th>
<th>Sequence of variables in which they entered in the regression equation</th>
<th>R²</th>
<th>Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Organic</td>
<td>1 pH</td>
<td>pH = -168.1 + 28.9*pH</td>
<td>0.52</td>
<td>ECₐ = -168.1 + 28.9*pH</td>
</tr>
<tr>
<td></td>
<td>2 pH, P</td>
<td>pH = -206.1 + 35.1<em>pH -0.03</em>P</td>
<td>0.63</td>
<td>ECₐ = -206.1 + 35.1<em>pH -0.03</em>P</td>
</tr>
<tr>
<td></td>
<td>3 pH, P, Mg</td>
<td>pH = -96.5 + 16.3<em>pH - 0.05</em>P + 0.02*Mg</td>
<td>0.71</td>
<td>ECₐ = -96.5 + 16.3<em>pH - 0.05</em>P + 0.02*Mg</td>
</tr>
<tr>
<td></td>
<td>4 pH, P, Mg, depth</td>
<td>pH = -98.2 + 15.8<em>pH - 0.06</em>P + 0.02<em>Mg + 0.47</em>depth</td>
<td>0.73</td>
<td>ECₐ = -98.2 + 15.8<em>pH - 0.06</em>P + 0.02<em>Mg + 0.47</em>depth</td>
</tr>
<tr>
<td></td>
<td>5 pH, P, Ca, Mg, depth</td>
<td>pH = -82.0 + 13.6<em>pH - 0.06</em>P - 0.001<em>Ca + 0.03 Mg + 0.40</em>depth</td>
<td>0.73</td>
<td>ECₐ = -82.0 + 13.6<em>pH - 0.06</em>P - 0.001<em>Ca + 0.03 Mg + 0.40</em>depth</td>
</tr>
<tr>
<td>Mineral</td>
<td>1 pH</td>
<td>pH = -6.05 + 7.38*pH</td>
<td>0.56</td>
<td>ECₐ = -6.05 + 7.38*pH</td>
</tr>
<tr>
<td></td>
<td>2 pH, P</td>
<td>pH = -1.29 + 4.87<em>pH + 0.17</em>P</td>
<td>0.69</td>
<td>ECₐ = -1.29 + 4.87<em>pH + 0.17</em>P</td>
</tr>
<tr>
<td></td>
<td>3 pH, P, K</td>
<td>pH = 5.56 + 4.71<em>pH + 0.15</em>P - 0.08*K</td>
<td>0.72</td>
<td>ECₐ = 5.56 + 4.71<em>pH + 0.15</em>P - 0.08*K</td>
</tr>
</tbody>
</table>
Whether the correlation or regression relationships are adequate for management will depend on their application. Ahmed and De Marsily (1987) reported that ECa and the related variable should have a value of the simple linear correlation of $r^2$0.70 ($R^2>0.49$) before the EC variable can be used to manage that specific variable in field. If the soil variable related to ECa directly affects the yield, then yield maps can also be used to calibrate ECa maps (Mueller et al. 2003). The relationship between ECa and pH in the bulked analysis for organic soil ($r=0.72$) and mineral soil ($r=0.75$) appears to be adequate for its application in soil pH management, but lower $r$ values ($<0.70$) in individual zones (EREc, Hillsboro farm, PPI and Hilliards) suggests that site-specific management strategies can be more effective in managing soil pH based on soil ECa maps. Additionally, the relationship of ECa with Mg ($r=0.74$) at EREC and soil depth ($r=0.78$) at Hillsboro farm indicates that it qualifies for use in management practices at these sites.

Soil pH in organic soils varied roughly from 6 to $>8$ in our data and most of the fields had pH $>7$. High soil pH limits the availability of soil nutrients to sugarcane (Ye et al. 2011) and has the potential to cause lower yields. Typically high soil pH in organic soils in Florida is managed by applying sulfur at the time of sugarcane planting. Currently sulfur is applied uniformly throughout the field and in-field variability of soil pH is ignored. Therefore, precise management of soil pH through ECa mapping may improve sugarcane yields and possibly save some fertilizer. Similarly, pH in mineral soil varied from $<5$ to $>8$, therefore, ECa mapping in pH management also has a potential to be used in mineral soils.

CONCLUSIONS

In conclusion, the correlations between ECa and any measured soil parameter were generally strong in some individual zones and weak in the others, and not consistent across the soil type. Hence, ECa may be more precisely used in management of these parameters at zonal or field level. In bulk soil, the correlations between ECa and soil pH were highest in both organic and mineral soil. Therefore, the use of ECa in soil pH management across a wide range of sugarcane fields in Florida can be further explored. Alternatively, ECa may be used in conjunction with soil sampling to determine the spatial variability of the soil variables and thereafter be used for precise management of different nutrients. Further research is needed to determine the relationship between ECa and sugarcane yield, and for the use of yield maps in ECa map calibrations.

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REFERENCES


Utilización de la medida de la conductividad eléctrica del suelo para mejorar el manejo de los nutrientes de la caña de azúcar en Florida

Resumen. La agricultura de precisión es considerada como uno de los enfoques más prometedores para la agricultura sostenible, pero requiere de métodos eficientes para medir con precisión las variaciones de las propiedades físicas y químicas del suelo dentro del campo. La conductividad eléctrica del suelo presenta la ventaja de ser una medida indirecta del estado del suelo, por lo que es un parámetro útil para el manejo de los nutrientes en los cultivos. En este estudio, se analizó la correlación entre la conductividad eléctrica del suelo (CE) y los parámetros químicos y físicos del suelo en diferentes áreas de la Florida. Se encontró una alta correlación entre la CE y los parámetros químicos del suelo, lo que sugiere que la CE puede ser utilizada como una herramienta valiosa para el manejo de los nutrientes en la agricultura de precisión. En consecuencia, la CE del suelo podría ser utilizada para determinar la variabilidad del suelo en el campo, lo que permitiría tomar decisiones más precisas y eficientes sobre el manejo de los nutrientes.

Mots-clés: Agricultura de precisión, CE del suelo, parámetros del suelo, correlación de Pearson, pH sol

Uso de la conductividad eléctrica aparente del suelo para mejorar el manejo de los nutrientes de caña de azúcar en la Florida

Resumen. La agricultura de precisión es considerada como uno de los enfoques más prometedores para la agricultura sostenible, pero requiere de métodos eficientes para medir con precisión las variaciones de las propiedades físicas y químicas del suelo dentro del campo. La conductividad eléctrica aparente del suelo (CE) es una medida indirecta del estado del suelo, por lo que es un parámetro útil para el manejo de los nutrientes en el cultivo de caña de azúcar. En este estudio, se analizó la correlación entre la CE y los parámetros químicos del suelo en diferentes áreas de la Florida. Se encontró una alta correlación entre la CE y los parámetros químicos del suelo, lo que sugiere que la CE puede ser utilizada como una herramienta valiosa para el manejo de los nutrientes en la agricultura de precisión. En consecuencia, la CE del suelo podría ser utilizada para determinar la variabilidad del suelo en el campo, lo que permitiría tomar decisiones más precisas y eficientes sobre el manejo de los nutrientes.

Mots-clés: Agricultura de precisión, CE del suelo, parámetros del suelo, correlación de Pearson, pH sol
suelos orgánicos, el grueso de los datos mostró correlaciones significativas entre la CEa con cada una de las variables, pH del suelo ($r = 0.72$), Mg ($r = 0.62$), Si ($r = 0.52$) y Ca ($r = 0.36$). En suelos minerales, también hubo correlaciones significativas, pH ($r = 0.75$), PMehlich-3 ($r = 0.73$), Ca ($r = 0.58$), y Si ($r = 0.48$). La agrupación de los campos en diferentes zonas en función de su ubicación cambió la correlación de las variables analizadas. El análisis de regresión paso a paso (PC-stepwise) indicó que el pH del suelo fue el principal contribuyente en la variabilidad de la CEa en ambos tipos de suelos. Los resultados mostraron que las correlaciones entre la CEa y los parámetros del suelo medidos no fueron consistentes a través de todas las zonas probadas en los campos. Por lo tanto, la CEa se puede utilizar con mayor precisión en el manejo de estos parámetros a nivel de zona o campo. En el grueso de los datos, las correlaciones entre la CEa y el pH del suelo fueron más altas en ambos tipos de suelo y se justifica la necesidad de una mayor exploración de los mapas de la CEa en el manejo del pH del suelo a través de una amplia variedad de campos de caña de azúcar en Florida. En forma alterna, la CEa se puede usar en conjunto con el muestreo de suelos para determinar la variabilidad espacial de los parámetros del suelo y, posteriormente, ser utilizada para el manejo preciso de los diferentes nutrientes. Se necesita más investigación para determinar la relación entre la CEa y el rendimiento de la caña de azúcar, y para el uso de mapas de rendimiento en el mapa de calibraciones de la Ecw.

**Palabras clave:** Agricultura de precisión, CE del suelo, variables del suelo, correlación de Pearson, pH del suelo