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Temporal Comparisons of Apparent Electrical Conductivity: A Case Study on Clay and Loam Soils in Mississippi

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Abstract

On-the-go soil sensors measuring apparent electrical conductivity (EC_a) in agricultural fields have provided valuable information to producers, consultants, and researchers on understanding soil spatial patterns and their relationship with crop components. Nevertheless, more information is needed in Mississippi, USA, on the longevity of EC_a measurements collected with an on-the-go soil sensor system. That information will be valuable to users interesting in employing the technology to assist them with management decisions. This study compared the spatial patterns of EC_a data collected at two different periods to determine the temporal stability of map products derived from the data. The study focused on data collected in 2016 and 2021 from a field plot consisting of clay and loam soils. Apparent electrical conductivity shallow (0 - 30 cm) and deep (0 - 90 cm) measurements were obtained with a mobile system. Descriptive statistics, Pearson correlation analysis, paired t-test, and cluster analysis (k-means) were used to compare the data sets. Similar trends were evident in both datasets; apparent electrical conductivity deep measurements were greater ($P < 0.05$) than the EC_a shallow measurements; a strong positive correlation ($P < 0.05$, $r > 0.90$) existed between the EC_a shallow and deep measurements. Also, a high correlation ($r \geq 0.79$) was observed between the EC_a measurements and the y-coordinates recorded by a global positioning system, indicating a spatial trend in the north and south direction (*vice versa*) of the plot. Comparable spatial patterns were observed between the years in the EC_a shallow and deep thematic maps developed via clustering. Apparent electrical conductivity data measurement patterns were consistent over the five years of this study. Thus the user has at least a five-year window from the first data collection to the next data collection to determine the relationship of the EC_a data to other agronomic variables.

Keywords

Time-Based, Clustering, Mapping

1. Introduction

Proximal or on-the-go sensors measuring soil electrical conductivity have shown good relationships with soil properties affecting crop production, including texture [1] [2], cation exchange capacity [3] [4], soil water content [3] [5], drainage condition [6], salinity [7] [8] [9], and subsoil characteristics [8] [10] [11]. The systems have shown promise in improving and developing soil boundaries because of their links to the global positioning system [2] [12]. Their popularity is increasing because of the various configurations available for integrating them with farm and commercial equipment [8] [9]. They can acquire large amounts of data cheaply and more quickly than manual surveys, thus, providing more detail on the spatial variability of an area [13]. Other systems such as ground penetrating radar [14], multispectral and hyperspectral imagery [6] [14], and time domain reflectometry [15] have shown potential to map soil spatial variability. Nevertheless, apparent electrical conductivity (EC_a) has been evaluated more than any other technique for studying soil spatial patterns [9] and has been recognized as a valuable tool to study soil spatial variability in agricultural settings [7] [16]. At the current rate, apparent electrical conductivity (EC_a) systems will be the staple equipment for mapping soil spatial variability now and in the immediate future.

Yet, a better understanding of the stability of EC_a measurements is needed so that users of the equipment have insight into the temporal stability of the readings. Using electromagnetic induction or the Veris mobile platform [17] [18] [19] [20] reported EC_a stability ranging from 2 months to 4 years. Also, more information is needed on comparing EC_a maps derived from over a period of time because the information would be valuable to farmers, consultants, and researchers interested in using the equipment to make management decisions.

Mississippi, USA, consists of various soils with different characteristics. Research is lacking in this area on the stability of apparent electrical conductivity measurements over time on soils used for agricultural production. The objective of this study was to compare spatial patterns of EC_a data collected at two different periods to determine the temporal stability of map products derived from the data. The study focused on data collected in 2016 and 2021 from a field plot consisting of clay and loam soils in Mississippi.

2. Materials and Methods

2.1. Study Area

The study was conducted at the United States Department of Agriculture, Agriculture Research Service Farm (−90.872157 Longitude, 33.446486 Latitude), near Stoneville, Mississippi, USA. The average precipitation and temperature were approximately 133 cm and 17.5˚C, respectively [21]. The field plot was 4.6 ha and consisted of the following soil types: Commerce silty clay loam, 0% to 2% slopes (Ch), Commerce very fine sandy loam, 0% to 2% slopes, Sharkey clay, 0.5% to 2% slopes, and Tunica clay, 0% to 2% slopes [22]. The field was in a continuous soybean (*Glycine max* L.) and corn (*Zea mays* L.) rotation. The plot was subjected to the standard agricultural practices of the area related to irrigation, weed treatment, and fertilization.

2.2. Data Collection

Apparent electrical conductivity readings were collected with the Veris MSP 3 (Veris Technologies, Salina, KS, USA, **Figure 1**) system. It collected shallow (0 - 30 cm) and deep (0 - 90 cm) measurements, representing the topsoil and subsoil. The EC_a system was moved through the field by a tractor. It used six coulters to penetrate the soil surface to a 6 cm depth. The coulters work in pairs with distinct functions. Coulters two and five injected the electrical current into the soil; coulters three and four recorded the EC shallow readings; coulters one and six recorded the deep readings. The sensor's output was in millisiemens (mS) per meter. A Garmin global positioning system recorded each measurement's latitude and longitude coordinates (WGS84). It recorded the location information when receiving differential global positioning data. A laptop computer inside the tractor's cab served as the data logger for the system. On March 29, 2016, and April 22, 2021, data were collected from 19 transects separated by 8 m within the field. The data were collected from bare soil.

2.3. Data Analysis

Post-processing of the data included assigning each measurement an identification number, changing the longitude and latitude coordinate information to the UTM coordinate system (UTM 15N, WGS84), and cleaning the data (*i.e.*, removal of negatives values, duplicated x-y coordinates, and outliers). Assigning point identification numbers, converting the latitude and longitude values, and

Figure 1. Veris MSP3 implement and tractor.

removing negative values and duplicate x-y coordinates were accomplished with QGIS (version 3.18.3-Zürich [23]).

Then, the data were transferred to the R software (R version 4.1.0, "Camp Pontanezen," [24]) to calculate histograms, boxplots, and descriptive statistics. That information was used to identify outliers and better understand the datasets. After the initial cleaning process, 1998 and 1765 data points were assessed, respectively, for analysis of the 2016 and 2021 datasets. Descriptive statistics (*i.e.*, mean, median, minimum, maximum, and coefficient of variation) and the paired t-test ($P < 0.05$) were used to compare the differences between the shallow and deep EC_a measurements. Pearson correlation coefficients ($P < 0.05$) were tabulated to evaluate the relationship between EC_a measurements and between the EC_a measurements and the x and y location coordinates. The relationship between the x and y coordinates and EC_a would give some insight into the directional trends in the dataset.

The cleaned data were clustered using the attributes clustering plug-in of QGIS. The following parameters were used for clustering: 1) method-k-means, 2) the number of times to repeat the classification-20, and 3) the threshold-0.00001. The clusters' summary statistics (*i.e.*, mean, median, minimum, and maximum values) were determined with the QGIS prepared initial statistical summary module. The cluster summary statistics were employed to assign a cluster to EC_a zones ranging from low to high. Note: the low to high assignment was based on the data obtained from this field. The final maps displayed in the figures were created with the QGIS software.

3. Results

The descriptive statistics are summarized in **Table 1** for both years. The EC_a shallow mean ($t = 117.85$, $df = 1997$, $P < 0.05$, 2016; $t = 106.01$, $df = 1764$, $P < 0.05$, 2021), median, minimum, and maximum values were less than the EC_a deep mean, median, minimum, and maximum values. The EC_a shallow readings were more variable than the EC_a deep readings according to the coefficient of variation values. Statistically significant positive correlation coefficients (**Table 2**)

Table 1. Descriptive statistics of apparent electrical conductivity shallow (EC_{as}) and deep (EC_{ad}) readings of the study site collected in 2016 and 2021.

Year	n[a]	Variable	Mean	Median	Min	Max	CV (%)
2016	1998	(EC_{as}) ($mS \cdot m^{-1}$)	68.7a	75.8	11.9	104.6	31.0
		(EC_{ad}) ($mS \cdot m^{-1}$)	86.8b	94.0	16.6	129.3	27.0
2021	1765	(EC_{as}) ($mS \cdot m^{-1}$)	68.5a	70.6	12.7	124.7	30.0
		(EC_{ad}) ($mS \cdot m^{-1}$)	87.9b	94.2	18.3	137.7	26.0

[a]n = number of samples, Min = minimum, Max = maximum, and CV = coefficient of variation; for each year, mean values followed by a different letter represent statistical significance at $P < 0.05$ according to paired t-test.

Table 2. Pearson correlation analysis between apparent electrical conductivity shallow (EC_{as}) and deep (EC_{ad}) measurements and x (x cor) and y (y cor) coordinates.

Year	n[a]	Variable	EC_{as}	EC_{ad}	x cor
2016	1998	EC_{as}			
		EC_{ad}	0.96*		
		x cor	−0.46*	−0.46*	
		y cor	0.81*	0.79*	−0.05*
2021	1765	EC_{as}			
		EC_{ad}	0.94*		
		x cor	−0.47*	−0.41*	
		y cor	0.82*	0.80*	−0.04

[a]n = number of samples, *statistically significant at $P < 0.05$.

were observed between each measurement data's EC_a shallow and deep readings. Also, both EC_a measures had a strong positive relationship with the y-coordinate, indicating a linear trend in the dataset based on direction.

Figure 2 and Figure 3 illustrate the map derived from clustering the EC_a shallow and deep values collected in 2016 and 2021, respectively. The lowest values were observed in the southeastern corner of the field. In contrast, the highest values were detected in the northern section of the plot. Low-Medium, Medium, and Medium-High values occurred from south to north in the field. A noticeable trend was observed on the maps; the values were similar in the southwest to the northeast direction (the other way around) and more variable in the south to the north direction (the other way around).

Descriptive statistics derived from the EC_a readings of the clusters are presented in Table 3. The clustering algorithm assigned the lowest number of points to the lowest zone for each dataset. These points were clustered in the southeastern section of the field (Figure 2 and Figure 3). The second-highest number of points was assigned to the Medium-High to High zones established by the clustering algorithm for this field. These areas were primarily in the northern part of the field (Figure 2 and Figure 3). The difference between the low and high clusters means was approximately 67.2 $mS \cdot m^{-1}$.

4. Discussion

The descriptive statistics patterns were consistent between the EC_a shallow and deep values measured in 2016 and 2021. That pattern was higher mean, median, minimum, and maximum values for the EC_a deep readings. Others documented the same pattern for soil EC_a shallow and deep readings in The Republic of Trinidad and Tobago [20], Belgium [25], Canada [26], and Spain [27]. Also, these findings agreed with the findings of [20] [28], who observed positive, statistically significant correlations between EC_a shallow and deep measurements. The correlation values between EC_a shallow and deep values were greater than 0.80,

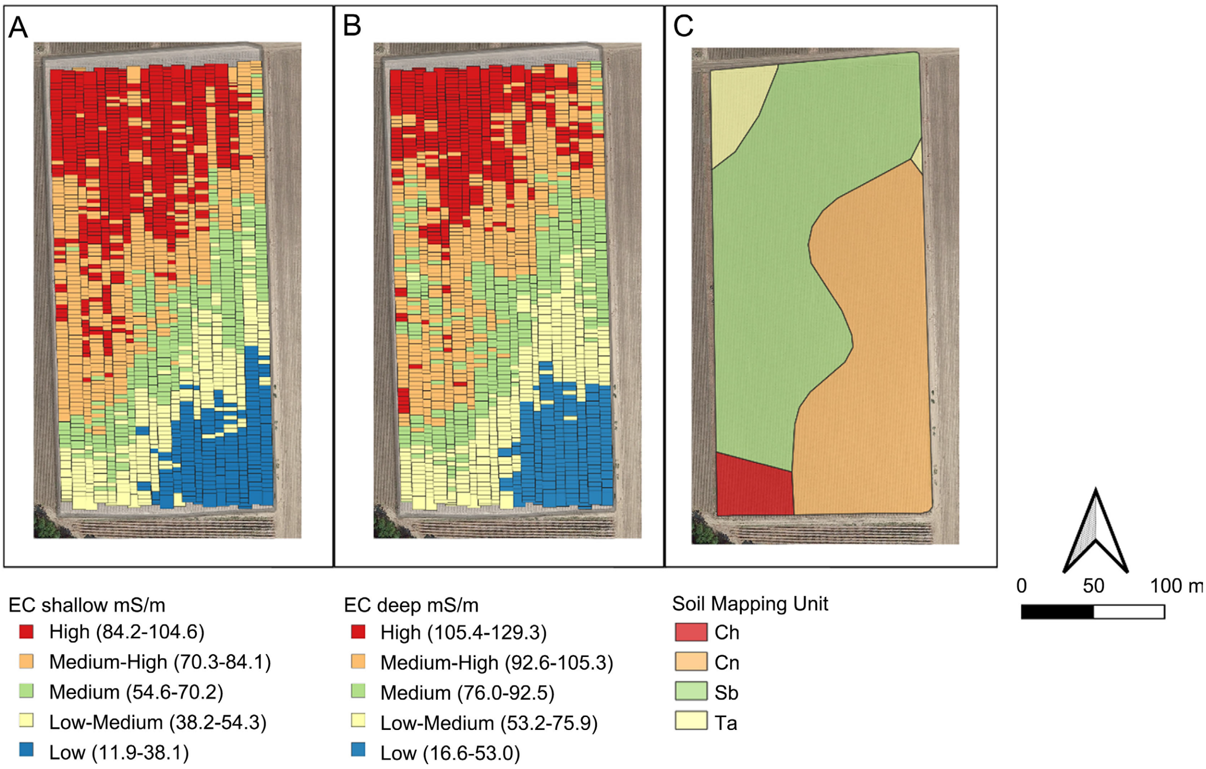

Figure 2. 2016 apparent electrical conductivity (EC) (A) shallow and (B) deep maps. (C) Soil survey map. Ch = Commerce silty clay loam, Cn = Commerce very fine sandy loam, Sb = Sharkey clay, and Ta = Tunica clay.

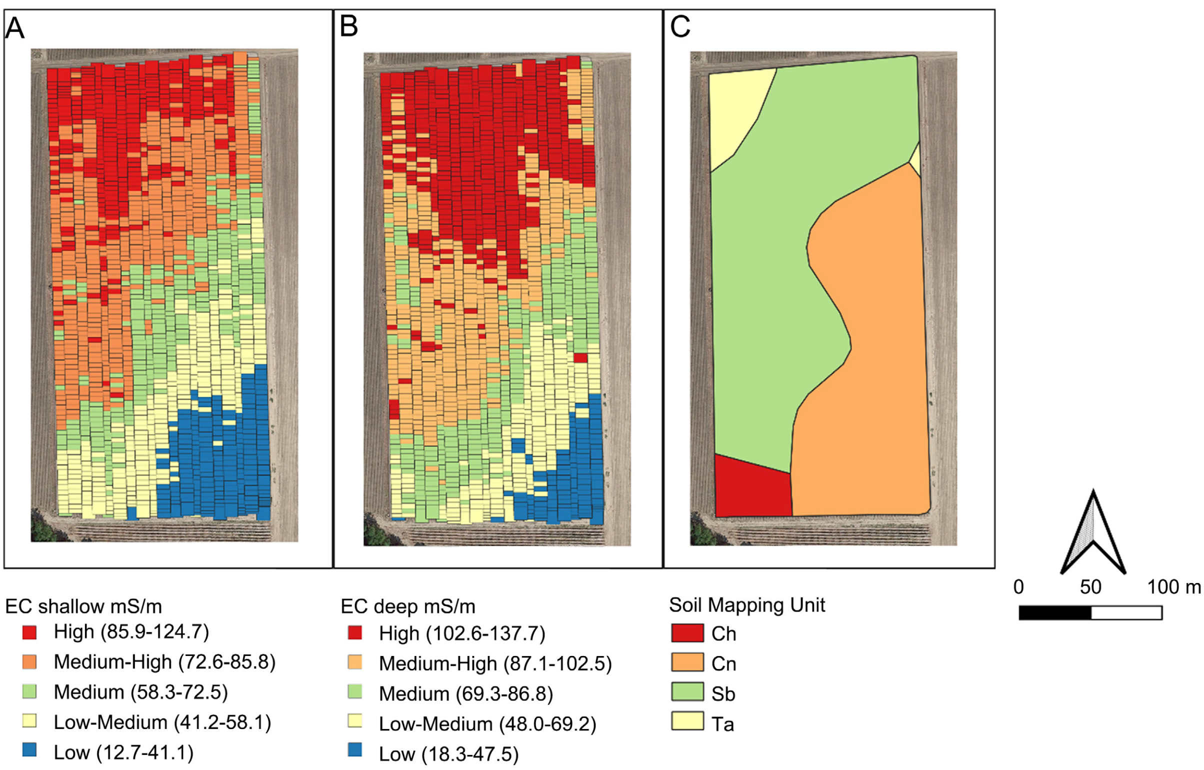

Figure 3. 2021 apparent electrical conductivity (EC) (A) shallow and (B) deep maps. (C) Soil survey map. Ch = Commerce silty clay loam, Cn = Commerce very fine sandy loam, Sb = Sharkey clay, and Ta = Tunica clay.

Table 3. Descriptive statistics of clusters derived from the apparent electrical conductivity shallow (EC_{as}) and deep (EC_{ad}) readings.

Study Site	Variable	Group	n[a]	Mean	Median	Min	Max
2016	EC_{as} ($mS \cdot m^{-1}$)	Low	230	29.0	30.3	11.9	38.1
		LM	301	46.7	47.0	38.2	54.3
		M	318	61.8	61.3	54.6	70.2
		MH	557	78.4	79.0	70.3	84.1
		High	592	89.9	89.2	84.2	104.6
	EC_{ad} ($mS \cdot m^{-1}$)	Low	223	39.7	41.0	16.6	53.0
		LM	340	65.8	66.3	53.2	75.9
		M	393	85.3	85.8	76.0	92.5
		MH	615	99.4	99.5	92.6	105.3
		High	427	111.3	110.2	105.4	129.3
2021	EC_{as} ($mS \cdot m^{-1}$)	Low	218	31.0	33.4	12.7	41.1
		LM	313	50.4	51.0	41.2	58.1
		M	317	65.7	65.5	58.3	72.5
		MH	565	79.7	80.0	72.6	85.8
		High	352	92.4	90.9	85.9	124.7
	EC_{ad} ($mS \cdot m^{-1}$)	Low	122	35.1	35.0	18.3	47.5
		LM	240	60.0	60.4	48.0	69.2
		M	311	78.4	78.1	69.3	86.8
		MH	537	95.3	95.5	87.1	102.5
		High	555	110.0	108.9	102.6	137.7

[a]n = number of samples, Min = minimum, Max = maximum, LM = low-medium, M = medium, and MH = medium-high.

indicating good quality data [9]; the ratio between the EC_a shallow and deep values were less than one signifying a regular soil profile, meaning for this field, soil properties that may be correlated with EC_a increases with depth [9].

The relationship between EC_a data and soil physical and chemical properties can be complex [8] [9]. Apparent electrical conductivity measurements have provided a general estimate of soil texture and have shown promise for mapping soil spatial variability [9]. On non-saline soils, increases in clay content were associated with increases in EC_a shallow and deep readings [19]. The soil in this study's field was not classified as being saline [22]. Hence, it was assumed that the northern portions of the field contained more clay than the southern sections of field. Points in the northern section of the field were grouped into the High EC_a zone. Furthermore, similarities and differences were apparent in the spatial patterns of the EC_a shallow and deep measurements.

Furrow irrigation was used to supply water to the crops grown in this field when needed. Yearly, the plot was irrigated from south to north. Some of the variability seen on the field maps could be attributed to irrigation. Furthermore, irrigation and other farm management practices would have affected the topsoil more than the subsoil, thus contributing to the topsoil having more variability than the subsoil (EC_a deep readings).

The results supported the theory that soil maps derived from the EC_a data should show the same pattern over time [19]. They are additional to the times reported in other studies reporting comparisons ranging from 2 months to 4 years [17] [18] [19] [20]. Others have reported positive results of using georeferenced EC_a data to be reliable for developing soil sampling strategies for non-point source pollutants [29], soil quality [30], and variations in crop yields [31]. Sampling schemes can be easily developed from the maps produced in this study.

The soil spatial variability map derived from the EC data is totally different from the field's USDA soil survey map. The EC_a map shows smoother transitions compared with the hard breaks between the soil survey map units. It is essential to point out that those differences are not new for maps derived with EC_a data. Nevertheless, the EC_a and USDA soil survey map provides important information for agricultural production.

5. Conclusion

The findings of this case study indicated that EC_a measurements have a longevity of at least five years, supporting backward compatibility between EC_a data and other types of data collected in the past. For example, a producer may have yield monitor data collected in 2020. However, apparent electrical conductivity data were not collected by the producer, consultant, etc., of the field until 2021. Thus, if the patterns observed on the 2021 EC_a maps are good for five years or more, then the producer, consultant, etc., should be able to evaluate the relationships between the different datasets. Future research will continue to focus on that point and others to determine the agronomic significance of EC_a maps derived from mobile sensors in agricultural fields in Mississippi, USA, over various time periods.

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Conflicts of Interest

The author declares no conflicts of interest regarding the publication of this paper.

References

[1] Heil, K. and Schmidhalter, U. (2012) Characterisation of Soil Texture Variability Using the Apparent Soil Electrical Conductivity at a Highly Variable Site. *Computers and Geosciences*, **39**, 98-110. https://doi.org/10.1016/j.cageo.2011.06.017

[2] Adamchuk, V.I., Hummel, J.W., Morgan, M.T. and Upadhyaya, S.K. (2004) On-the-Go Soil Sensors for Precision Agriculture. *Computers and Electronics in Agriculture*, **44**, 71-91. https://doi.org/10.1016/j.compag.2004.03.002

[3] Koraseath, A., Riley, H., Kvaerno, S.H. and Vestgarden, L.S. (2008) Relations between a Commercial Soil Survey Map Based on Soil Apparent Electrical Conductivity (ECa) and Measured Soil Properties on a Morainic Soil in Southeast Norway. In: Allred, B., Daniels, J.J. and Reza Ehsani, M., Eds., *Handbook of Agricultural Geophysics*, CRC Press, Boca Raton, 247-254.

[4] Triantafilis, J., Lesch, S.M., Lau, K.L. and Buchanan, S.M. (2009) Field Level Digital Soil Mapping of Cation Exchange Capacity Using Electromagnetic Induction and a Hierarchical Spatial Regression Model. *Soil Research*, **47**, 651-663. https://doi.org/10.1071/SR08240

[5] Hezarjaribi, A. and Sourell, H. (2007) Feasibility Study of Monitoring the Total Available Water Content Using Non-Invasive Electromagnetic Induction-Based and Electrode-Based Soil Electrical Conductivity Measurements. *Irrigation and Drainage*, **56**, 53-65. https://doi.org/10.1002/ird.289

[6] Liu, J., Pattey, E., Nolin, M.C., Miller, J.R. and Ka, O. (2008) Mapping Within-Field Soil Drainage Using Remote Sensing, DEM and Apparent Soil Electrical Conductivity. *Geoderma*, **143**, 261-272. https://doi.org/10.1016/j.geoderma.2007.11.011

[7] Corwin, D. (2008) Past, Present, and Future Trends of Soil Electrical Conductivity Measurement Using Geophysical Methods. In: Allred, B., Daniels, J.J. and Reza Ehsani, M., Eds., *Handbook of Agricultural Geophysics*, CRC Press, Boca Raton, 17-44.

[8] Doolittle, J.A. and Brevik, E.C. (2014) The Use of Electromagnetic Induction Techniques in Soils Studies. *Geoderma*, **223**-**225**, 33-45. https://doi.org/10.1016/j.geoderma.2014.01.027

[9] Corwin, D.L. and Scudiero, E. (2020) Field-Scale Apparent Soil Electrical Conductivity. *Soil Science Society of America Journal*, **84**, 1405-1441. https://doi.org/10.1002/saj2.20153

[10] Anderson-Cook, C.M., Alley, M.M., Roygard, J.K.F., Khosla, R., Noble, R.B. and Doolittle, J.A. (2002) Differentiating Soil Types Using Electromagnetic Conductivity and Crop Yield Maps. *Soil Science Society of America Journal*, **66**, 1562-1570. https://doi.org/10.2136/sssaj2002.1562

[11] Sudduth, K.A., Kitchen, N.R., Myers, D.B. and Drummond, S.T. (2010) Mapping Depth to Argillic Soil Horizons Using Apparent Electrical Conductivity. *Journal of Environmental and Engineering Geophysics*, **15**, 135-146. https://doi.org/10.2113/JEEG15.3.135

[12] Johnson, C.K., Mortensen, D.A., Wienhold, B.J., Shanahan, J.F. and Doran, J.W. (2003) Site-Specific Management Zones Based on Soil Electrical Conductivity in a Semiarid Cropping System. *Agronomy Journal*, **95**, 303-315. https://doi.org/10.2134/agronj2003.3030

[13] Mueller, L., Schindler, U., Mirschel, W., Shepherd, T.G., Ball, B.C., Helming, K., Rogasik, J., Eulenstein, F. and Wiggering, H. (2011) Assessing the Productivity Function of Soils. In: Lichtfouse, E., Hamelin, M., Navarrete, M. and Debaeke, P., Eds., *Sustainable Agriculture*, Vol. 2, Springer, Dordrecht, 743-760.

https://doi.org/10.1007/978-94-007-0394-0_33

[14] Ciampalini, A., André, F., Garfagnoli, F., Grandjean, G., Lambot, S., Chiarantini, L. and Moretti, S. (2015) Improved Estimation of Soil Clay Content by the Fusion of Remote Hyperspectral and Proximal Geophysical Sensing. *Journal of Applied Geophysics*, **116**, 135-145. https://doi.org/10.1016/j.jappgeo.2015.03.009

[15] Huisman, J.A., Snepvangers, J.J.J.C., Bouten, W. and Heuvelink, G.B.M. (2002) Mapping Spatial Variation in Surface Soil Water Content: Comparison of Ground-Penetrating Radar and Time Domain Reflectometry. *Journal of Hydrology*, **269**, 194-207. https://doi.org/10.1016/S0022-1694(02)00239-1

[16] Lück, E., Gebbers, R., Ruehlmann, J. and Spangenberg, U. (2009) Electrical Conductivity Mapping for Precision Farming. *Near Surface Geophysics*, **7**, 15-26. https://doi.org/10.3997/1873-0604.2008031

[17] Medeiros, W.N., de Queiroz, D.M., Valente, D.S.M., Pinto, F. and Melo, C.A.D. (2016) The Temporal Stability of the Variability in Apparent Soil Electrical Conductivity. *Bioscience Journal*, **32**, 150-159.

[18] Clay, D.E., Chang, J., Malo, D.D., Carlson, C.G., Reese, C., Clay, S.A., Ellsbury, M. and Berg, B. (2001) Factors Influencing Spatial Variability of Soil Apparent Electrical Conductivity. *Communications in Soil Science and Plant Analysis*, **32**, 2993-3008. https://doi.org/10.1081/CSS-120001102

[19] Farahani, H.J. and Buchletter, G.W. (2004) Temporal Stability of Soil Electrical Conductivity in Irrigated Sandy Fields in Colorado. *Transactions of the American Society of Agricultural Engineers*, **47**, 79-90. https://doi.org/10.13031/2013.15873

[20] De Caires, S.A., Wuddivira, M.N. and Bekele, I. (2015) Spatial Analysis for Management Zone Delineation in a Humid Tropic Cocoa Plantation. *Precision Agriculture*, **16**, 129-147. https://doi.org/10.1007/s11119-014-9366-5

[21] WorldClimate (n.d.) Average Weather Data for Stoneville, Mississippi. http://www.worldclimate.com/climate/us/mississippi/stoneville

[22] Soil Survey Staff, Natural Resources Conservation Service, United States Department of Agriculture (n.d.). Web Soil Survey. https://www.nrcs.usda.gov/wps/portal/nrcs/detail/soils/survey/?cid=nrcseprd1464818

[23] QGIS Development Team (2021) QGIS Geographic Information System. Open Source Geospatial Foundation Project. http://qgis.osgeo.org

[24] R Core Team (2021) R: A Language and Environment for Statistical Computing. R Foundation for Statistical Computing, Vienna.

[25] Vitharana, U.W.A., Van Meirvenne, M., Simpson, D., Cockx, L. and De Baerdemaeker, J. (2008) Key Soil and Topographic Properties to Delineate Potential Management Classes for Precision Agriculture in the European Loess Area. *Geoderma*, **143**, 206-215. https://doi.org/10.1016/j.geoderma.2007.11.003

[26] Perron, I., Cambouris, A.N., Chokmani, K., Vargas Gutierrez, M.F., Zebarth, B.J., Moreau, G., Biswas, A. and Adamchuk, V. (2018) Delineating Soil Management Zones Using a Proximal Soil Sensing System in Two Commercial Potato Fields in New Brunswick, Canada. *Canadian Journal of Soil Science*, **98**, 724-737. https://doi.org/10.1139/cjss-2018-0063

[27] Koganti, T., Moral, F.J., Rebollo, F.J., Huang, J. and Triantafilis, J. (2017) Mapping Cation Exchange Capacity Using a Veris-3100 Instrument and InvVERIS Modelling Software. *Science of the Total Environment*, **599-600**, 2156-2165. https://doi.org/10.1016/j.scitotenv.2017.05.074

[28] Ezrin, M., Amin, M., Anuar, A. and Aimrun, W. (2010) Relationship between Rice Yield and Apparent Electrical Conductivity of Paddy Soils. *American Journal of Applied Sciences*, **7**, 63-70. https://doi.org/10.3844/ajassp.2010.63.70

[29] Corwin, D.L., Carrillo, M.L.K., Vaughan, P.J., Rhoades, J.D. and Cone, D.G. (1999) Evaluation of a GIS-Linked Model of Salt Loading to Groundwater. *Journal of Environmental Quality*, **28**, 471-480. https://doi.org/10.2134/jeq1999.00472425002800020012x

[30] Johnson, C.K., Doran, J.W., Duke, H.R., Wienhold, B.J., Eskridge, K.M. and Shanahan, J.F. (2001) Field-Scale Electrical Conductivity Mapping for Delineating Soil Condition. *Soil Science Society of America Journal*, **65**, 1829-1837. https://doi.org/10.2136/sssaj2001.1829

[31] Corwin, D.L., Lesch, S.M., Shouse, P.J., Soppe, R. and Ayars, J.E. (2003) Identifying Soil Properties that Influence Cotton Yield Using Soil Sampling Directed by Apparent Soil Electrical Conductivity. *Agronomy Journal*, **95**, 352-364. https://doi.org/10.2134/agronj2003.3520