THE ULTIMATE SOIL SURVEY IN ONE PASS: SOIL TEXTURE, ORGANIC MATTER, PH, ELEVATION, SLOPE, AND CURVATURE

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ABSTRACT

The goal of accurately mapping soil variability preceded GPS-aided agriculture, and has been a challenging aspect of precision agriculture since its inception. Many studies have found the range of spatial dependence is shorter than the distances used in most grid sampling. Other studies have examined variability within government soil surveys and concluded that they have limited utility in many precision applications. Proximal soil sensing has long been envisioned as a method that would provide the full field coverage needed to accurately delineate soil productivity zones. Of the various sensing technologies, soil electrical conductivity (EC) sensing has seen the most widespread use, and adoption is increasing. The soil EC signal responds primarily to soil texture changes and in cases where salinity levels are elevated, it delineates those areas as well. While soil texture is an important factor in crop production, there are other factors to consider including organic matter, soil pH, and landscape position. A new suite of soil sensors that simultaneously measures these properties has been commercialized by Veris Technologies. To evaluate the accuracy of the sensors, a multi-state, multi-field study was conducted, and sensor readings were validated with lab-analyzed soil samples. Results show strong correlation between sensors and lab data, and overlaying sensor maps with soil surveys and 1 ha grid cells confirms the need for detailed soil mapping.

Keywords: proximal, soil, sensing, organic matter, pH, texture, topography

INTRODUCTION

U.S. federal funding for soil surveys began in the late 1800's, and by the 1980's most of the main agricultural areas in the U.S. had been surveyed. The purpose of these surveys is to provide soil information to planners, engineers, builders, specialists in recreation, wildlife management, waste disposal, as well as to the agricultural community.

The properties relevant to agriculture delineated in these surveys soil include soil texture, organic matter (OM), cation-exchange capacity (CEC), soil pH, and soil depths. In most cases the range of these descriptions is fairly broad. For example, the soil properties in the top 35 cm for Drummer, the state soil of Illinois are listed as pH 5.6-7.8, organic matter 4.0-7.0, and CEC 24-35 (Natural Resources Conservation Service, 2001). Most surveys were completed at a 1:15,840 to 1:24,000 scale, which did not identify areas smaller than 1-2.5 ha. Recently, USDA soil surveys have been digitized and most are available on-line. This improves access to the original maps, but with few exceptions, fields have not been re-surveyed since the advent of a global positioning systems (GPS) and other advanced precision agriculture technology. As a result, the level of quantitative soil property information, and geo-referenced mapping that could identify inclusions and provide precise line placement is not available from the USDA surveys.

Research has confirmed these limitations. For example, one study found that in a field with two major and two minor soils, the major soils were correctly identified by the soil survey in only 63% of the cases, while the two minor soils were correctly identified in less than 33% of the cases (Brevik et al., 2003). The USDA digital soil survey website offers this warning when most field scale surveys are downloaded: “You have zoomed in beyond the scale at which the soil map for this area is intended to be used…Enlargement of maps beyond the scale of mapping can cause misunderstanding of the detail of mapping and accuracy of soil line placement. The maps do not show the small areas of contrasting soils that could have been shown at a more detailed scale”.
(websoilsurvey.nrcs.usda.gov/app/WebSoilSurvey.aspx)

Proximal or on-the-go soil sensors using GPS have the capability of improving the delineation of soil boundaries (Adamchuk et al., 2004). The first proximal soil sensors were introduced in the 1990’s and are now being used in many crop production systems. The initial proximal soil sensor that was developed into a commercial mapping system was for mapping soil electrical conductivity (Lund, et al., 1998). Soil EC measurements correlate with soil properties that affect crop productivity, including soil texture, cation exchange capacity, drainage conditions, salinity and subsoil characteristics (Grisso et al., 2009).

A soil pH sensor was commercialized nearly a decade ago (Adamchuk, et al., 2005). Soil pH is an important factor in crop production. Nutrient usage, crop growth, legume nodulation, and herbicide activity are all affected by the pH of the soil (Logsdon et al., 2008). Numerous studies have shown that the range of spatial dependence for pH can be significantly shorter than typical grid-sampling distances (McBratney and Pringle, 1997), and variations of 2 pH units can occur over distances less than 12 m apart (Bianchini and Mallarino, 2002). Within many 1 ha grids, there is a wide range of pH values, often ranging from soils that call for lime to soils that are already extremely high in pH (Brouder et al., 2005).

Recently, a proximal sensor for soil organic matter became commercially available (Lund and Maxton, 2011). Soil OM affects the chemical and physical properties of the soil and its overall health. It’s a key component of structure and porosity, affecting moisture holding capacity, the diversity and biological activity of soil organisms, and plant nutrient availability (Bot and Benites, 2005).

Topography and landscape position frequently exerts a significant influence on soil properties and productivity, and can augment proximal soil sensing (Kitchen et al., 2003). With the advent of real-time-kinematic (RTK) and other high-grade GPS receivers, precise topographical measurements can be acquired simultaneously and co-located with proximal soil sensor readings.

Recently, a new multi-sensor platform was commercialized that records soil EC, OM, and pH from proximal sensors along with topography data. The objective of this study was to evaluate its performance on several fields in four mid-western states, comparing results with lab-analyzed samples and with soil surveys and grid sampling.

MATERIALS AND METHODS

Research sites

This research covered 347 ha on 8 fields in the states of Illinois, Iowa, Kansas and Nebraska having a wide range of soil types and textures. 74 soil cores were sampled for OM, CEC and pH analysis from these fields. The soil samples with six 0-15 cm deep cores were collected within a 10 m radius and composited, and tested in the soil testing lab of Kansas State University and the Midwest Laboratories testing lab in Nebraska. Information about the research fields in 4 states is shown in Table 1.

Table 1 Information of the research fields in 4 states.

Field name	Location: county	Area (ha)	No. of Sample	Soil series
IA1	Pocahontas	60	12	Clarion loam, Webster, Canisteo & Nicollet clay loam
IA2	Kossuth	60	15	Clarion & Nicollet loam, Canisteo clay loam
IL1	Mason	30	4	Canisteo loam, Selma clay loam, Ridgeville sandy loam
IL2	McLean	32	4	Sable & Harpster silty clay loam
KS1	Saline	64	8	Longford silt loam, Crete silt loam, Wells loam
KS2	Doniphan	50	21	Contrary-Monona silt loams
NE1	Washington	22	5	Kezan-Kennebec silt loams, Judson & Marshall-Pohocco silty clay loam
NE2	Washington	29	5	Marshall-Pohocco silty clay loams, Marshall silty clay loam

Field equipment

Fig. 1 shows the Veris on-the-go soil EC, OM and pH sensing system (MSP3^{TM}). The implement contains six coulter electrodes for EC measurements, a specially-configured row unit for optical measurements, and a soil sampling shoe and ion selective electrodes (ISEs) for pH measurements. The EC module measures EC values directly using rolling coulters inserted into the soil. The system maps soil texture based on the established practice of measuring soil EC in situ, whereby smaller soil particles such as clay conduct more current than larger silt and sand particles (Williams and Hoey, 1987). One pair of coulters in the module injects an electrical current into the soil and the other coulters measure the voltage change. The measurement from one pair is for a “shallow” EC (0–30 cm) and the other is for “deep” EC (0–90 cm).

The optical sensor module maps soil underneath crop residue and the soil surface. Soil measurements are acquired through a sapphire window on the bottom of a furrow ‘shoe’. Soil OM relates closely to productivity, and is a useful property for variable rate population and nitrogen. (Bauer and Black, 1994; Fleming et al., 2004). The device consists of several components including an opening coulter for cutting crop residue, a depth-control row unit, an optical module, electronics for signal conditioning, a data logger and a GPS. The optical module consists of a single photodiode, two light sources with a red light-emitting diode (LED) of 660 nm and a NIR LED of 940 nm wavelength. The modulated light is directed through the sapphire window onto the soil. The reflected light is then received by the photodiode, and converted to a modulated voltage. The converted modulated voltage is processed through the signal conditioning circuit, which separates each source of reflected light from the photodiode signal and converts the modulated voltage to a direct current (DC) voltage. The DC voltage is processed and then the output is sent serially to a laptop computer for data logging.

During field operation, the soil pH mapping unit automatically collects a soil sample and records its geographic position while traveling across the field. Measurements are conducted using antimony ion-selective pH electrodes. Every recorded measurement represents an average of the outputs produced by two independent electrodes, which allows in-field cross validation of electrode performance as well as filtering out erroneous readings. Extracted on-the-go soil cores are brought into direct contact with the electrodes and held in place for 7–20 s (depending on the electrode response). At the end of each measuring cycle, both electrodes are rinsed with water. Simultaneously, a new sample is obtained to replace the analyzed soil. The average cycle time is approximately 10 s, but may vary according to the selected electrode stabilization criterion and electrode performance. All geo-referenced data are saved in delimited text files.

Fig. 1. On-the-go soil EC, OM, and pH sensing systems (MSP3^{TM}).

Topography calculations

Topographic attributes were calculated from elevation measurements collected simultaneously with the on-the-go sensing systems using a real-time kinematic GPS. Terrain slope was calculated based on the direction of steepest ascent or descent in the sensing location and represented as a slope angle from zero (horizontal) to 90 (vertical) degrees. Curvature is a measure of the curvature of contours, which reflects the rate of change of the terrain aspect angle measured in the horizontal plane. Negative values mean divergent water flow over the surface, and positive values mean convergent flow (Surfer, 2002). For obtaining slope and curvature values, grids were generated in each field after converting the longitude and latitude to meters in the Universal Transverse Mercator (UTM) system. The distance between grids was set to 10 m. The elevation data obtained with EC and OM at the original points was interpolated into the grids by a Gaussian kernel weighting method (Christy, 2008). Slope and curvature were then calculated by classical terrain modelling algorithms at each grid (Moore et al., 1993).

Data logging and processing

All sensor data were acquired on a Windows PC with Veris SoilViewer software (Fig 2). Sensor views, colors, and data ranges are user-selectable and data is visually screened for instant data quality feedback.

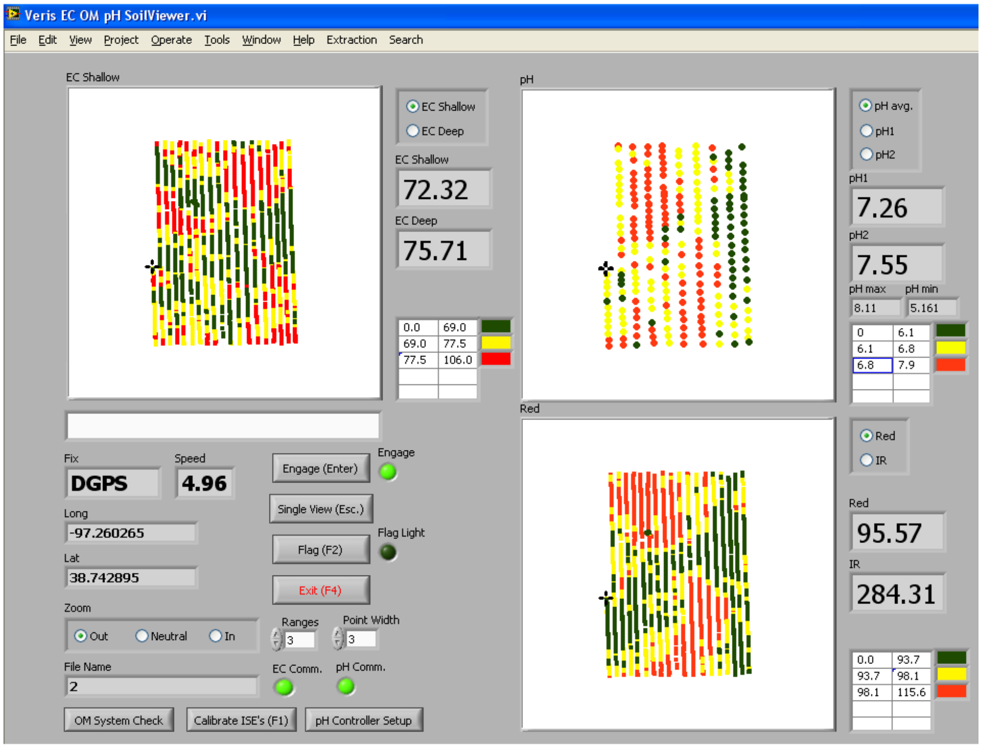

Fig. 2. SoilViewer EC, OM and pH mapping software.

The raw data obtained by the on-the-go soil sensing systems need data processing in order to remove outliers. GPS error outliers were removed when a sensing point is out of 100 m radius from the previous measurement location. Optical system outliers from the normal ranges of soil reflectance were filtered. Global field outliers that are not within three times the standard deviation from the mean of all field data, and local field outliers, when the value of optical data at each measurement location is greater than two times the standard deviation from the mean at the neighboring 10 sensing points, were also removed.

Using data collected by the optical and soil EC sensors, along with topographical data, a calibration routine with multivariate regression (MVR) programmed with LabVIEW (National Instruments Corp., Austin, TX, USA) tests every combination of sensor variables for their relationship to OM and CEC for fields with 10 or more lab-analyzed calibration samples. On fields with less than 10 samples, single variable linear regressions were performed to avoid overfitting, using each sensor variable and lab-analyzed measurements. The routine performs a leave one out cross validation to the lab analyzed OM and CEC. Calibration statistics such as R^2, RMSE (root mean squared error), standard deviation, and RPD (Ratio of Prediction to Deviation = standard deviation/ root mean squared error of prediction) are calculated and reported. The calibration with the highest RPD is used to apply to the field data to produce the OM and CEC estimations. RPD is a useful measure of fit to compare results from datasets with different degrees of variability (Hummel et al., 2001; Lee et al., 2009). Chang et al. (2001) categorized RPD ranges as high (> 2.0), medium (1.4-2.0) and low (< 1.4) to classify the ability of NIR to estimate soil properties. A higher RPD indicates a more accurate prediction.

RESULTS

Table 2 shows descriptive statistics of OM, CEC and pH lab values for the research fields. Iowa fields have wide ranges of soil organic matter contents of 2.4 -5.8 % and CEC values of 15.3-33.9 meq $100g^{-1}$, and Kansas soils have narrow ranges in the soil properties with 1.0-2.8 % for OM and 15.4-24.4 meq $100g^{-1}$ for CEC. CEC for Nebraska fields were not obtained. Illinois and Iowa fields have high OM values up to 5.8 %, and Kansas and Nebraska fields have relatively low OM values. The soil pH values in each the 8 fields have a similar range, with a difference of at least 2 points within each field.

Table 2 Descriptive statistics of OM, CEC and pH lab values for the research fields.

Field	OM (%)			CEC (meq $100g^{-1}$)			pH		
	Mean	Range	SD	Mean	Range	SD	Mean	Range	SD
IA1	3.9	2.4-5.7	1.2	23.2	15.3-33.9	6.8	6.8	5.6-7.8	0.7
IA2	4.4	2.8-5.8	1.1	23.4	15.7-30.0	4.7	6.7	5.2-7.9	0.9
IL1	3.3	0.2-5.1	1.8	24.4	8.3-40.0	10.8	7.2	6.3-8.3	1.2
IL2	4.7	4.4-5.1	0.1	32.2	26.9-40.0	5.6	6.8	5.0-8.0	1.4
KS1	1.8	1.5-2.4	0.3	19.2	15.4-24.4	3.0	6.7	5.2-7.8	1.0
KS2	2.0	1.0-2.8	0.5	18.0	13.4-22.5	2.1	5.6	4.7-7.8	1.0
NE1	2.3	1.4-4.0	1.0	-	-	-	6.8	5.6-8.2	1.2
NE2	1.8	1.0-2.4	0.6	-	-	-	6.1	5.4-8.4	1.3

Table 3 shows calibration results for OM, CEC and pH. IL1 had the highest R^2 and RPD of 0.94 and 4.62 for OM. IL2 and KS1 fields were not as highly correlated, with R^2 of 0.54 and 0.44, and RPD of 1.70 and 1.43, respectively, although they had the lowest RMSE. This may be because of narrow ranges of variability in these fields as seen in Table 2. For CEC, all fields except KS2 had good results with RPD of 1.98 or higher. IL1 had the highest R^2 and RPD of 0.94 and 4.58. IL2 had the highest correlation and RPD for pH.

Table 3 Calibration results for OM, CEC and pH for the research fields.

Field	OM (%)			CEC (meq $100g^{-1}$)			pH		
	R^2	RMSE	RPD	R^2	RMSE	RPD	R^2	RMSE	RPD
IA1	0.84	0.48	2.61	0.84	2.59	2.63	0.58	0.45	1.61
IA2	0.92	0.29	3.71	0.88	1.65	2.93	0.77	0.47	2.19
IL1	0.94	0.31	4.62	0.94	1.92	4.58	0.82	0.34	2.70
IL2	0.54	0.18	1.70	0.66	2.85	1.98	0.98	0.15	8.25
KS1	0.44	0.20	1.43	0.93	0.77	3.93	0.89	0.31	3.21
KS2	0.78	0.21	2.19	0.17	1.89	1.12	0.67	0.18	1.80
NE1	0.92	0.25	4.01	-	-	-	0.94	0.25	4.47
NE2	0.81	0.23	2.55	-	-	-	0.91	0.34	3.75

The dense coverage provide by proximal soil sensors is best illustrated with sensor point data maps. Typically, more than 200 EC and optical measurements are collected per hectare and 10-20 pH sensor readings per ha. Fig 3 shows soil CEC, OM and pH maps for KS1 estimated by the multiple sensors with lab-analyzed soil samples overlaid. The data have been collected at an adequate spatial scale to show pass-to-pass repeatability. The spatial structure of the soil properties is discernible even without interpolating or other manipulation.

Fig. 4 shows interpolated sensor maps for IA1 of soil CEC, OM and pH estimated by the on-the-go sensing system, with 1 ha (2.5 acre) grid lines overlaid. There is a wide range of variability within many of the grid cells with CEC values ranging 10 meq $100g^{-1}$, and OM 1-2 %. The pH within-grid variations range from spots within the grid requiring no lime to acid areas that would require over 4 tons/ha.

Fig. 5 shows OM and pH scatter plots for all the datasets in the research fields. Correlation between lab measured and estimated values showed very high for OM (R^2 = 0.95) and pH (R^2 = 0.85). Both datasets had low RMSE with 0.30 and 0.43, respectively.

Fig. 6 shows scatter plots between lab-measured CEC and sensed EC values, and between lab-measured CEC and estimated CEC by the EC and OM sensors. EC values alone did not have high correlations to CEC (R^2 = 0.41), however EC along with optical sensors showed high correlation with R^2 of 0.90.

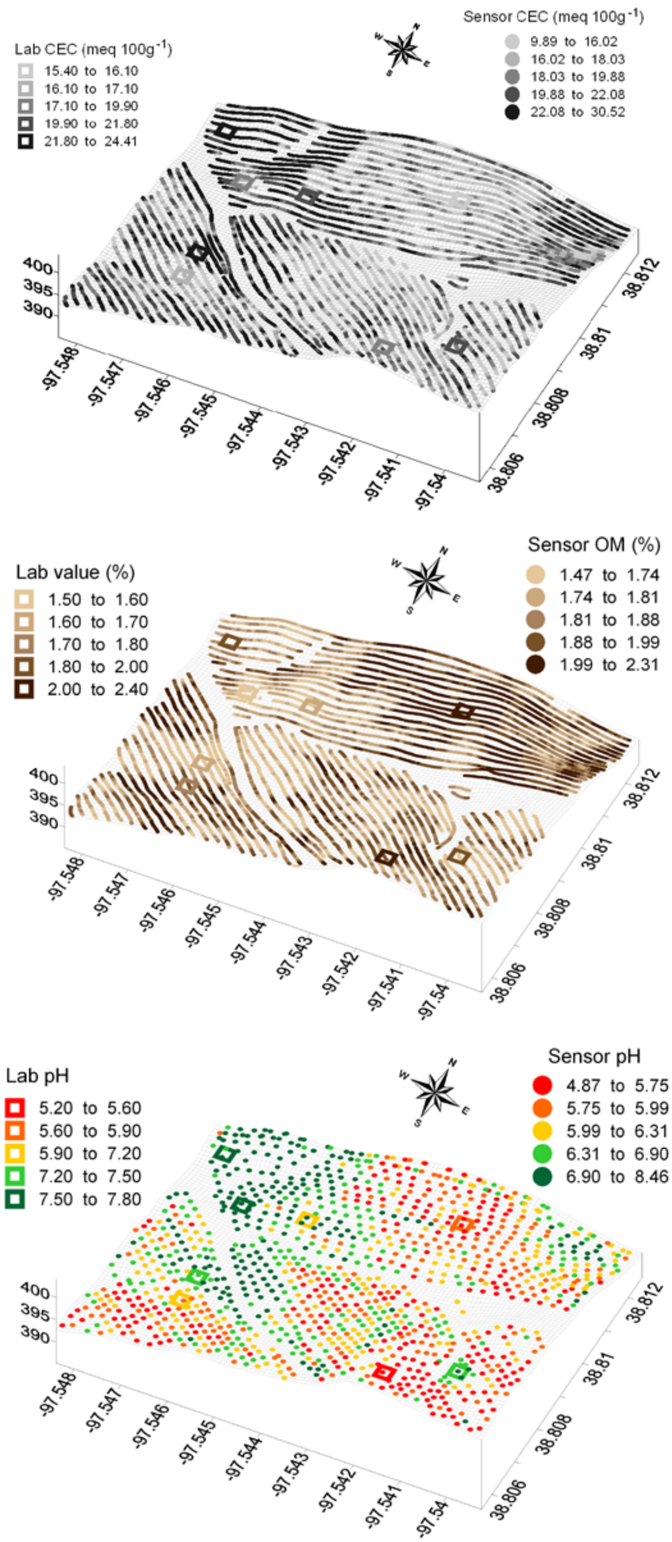

Fig. 3. Soil CEC, OM and pH maps from proximal sensing systems with lab-analyzed soil samples overlaid for KS1.

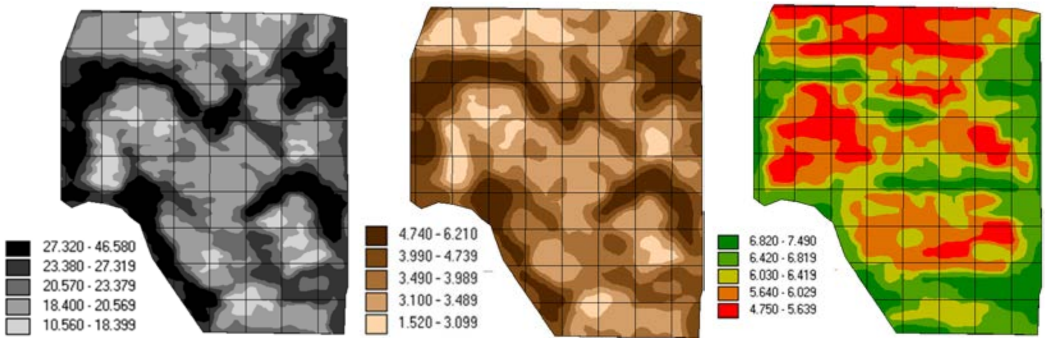

Fig. 4. Soil CEC, OM and pH maps by the on-the-go sensing systems on 2.5 acre grids for IA1.

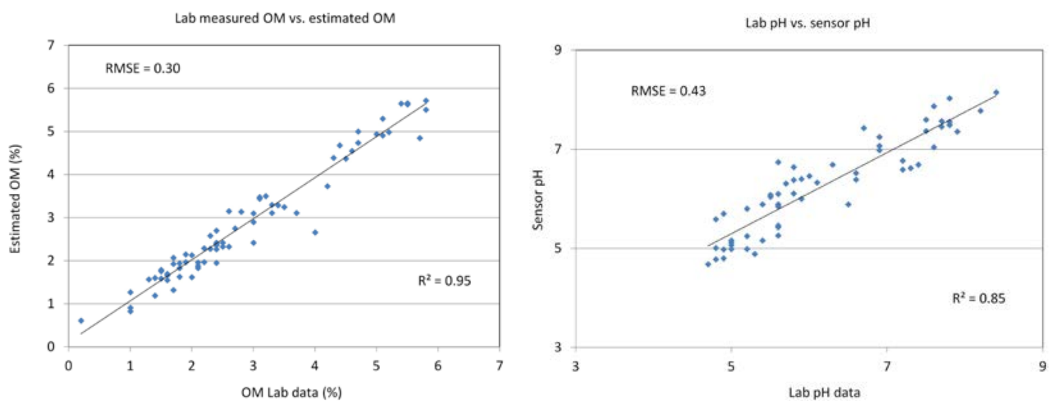

Fig. 5. Soil organic matter and pH scatter plots for research fields in 4 states.

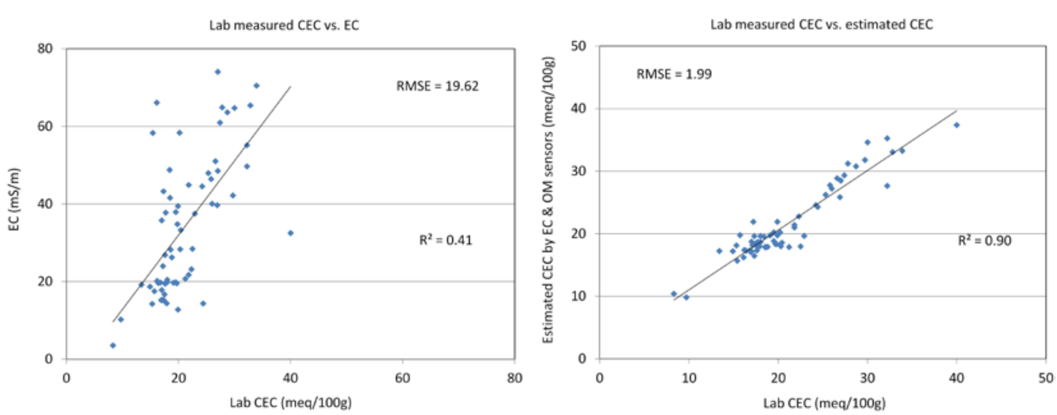

Fig. 6. Scatter plots for EC and estimated CEC with lab measured CEC.

DISCUSSION

The results presented above show that readings from the multi-sensor system correlated well with lab-analyzed samples. The fields with the lowest OM correlation, IL2 and KS1, had a very low level of OM variability with standard deviations of 0.1 and 0.3 respectively. Even with low R^2 and RPD scores on those fields, the OM RMSEs were the lowest of all fields. CEC results showed a similar response, with sensors achieving better results in more variable fields. The combination of EC and optical measurements correlated significantly better to CEC than either sensor individually. This could be expected, as CEC is affected by both soil texture and organic matter. Proximal pH sensor readings correlated well with lab pH on all project fields. Interestingly, the IL2 and KS1 fields that had low OM variability had some of the highest pH variations and best RPDs with pH sensors. This illustrates the value of a multi-sensor approach, as having several properties mapped at a dense spatial scale increases the likelihood of uncovering whatever soil property variations may be present. The improvement in CEC predictions by including other sensor data versus soil EC alone, as shown in Fig. 6, further illustrates the benefits of mapping with multiple soil sensors.

In order to compare the sensor maps and the USDA soil surveys for these fields, and attempt to quantify differences between the approaches, it is instructive to use the self-described soil survey limitations listed earlier. These are: 1) the wide range of soil property values listed for each soil type, 2) size of allowed inclusions within a map unit, and 3) line placement accuracy. First, the range found within soil survey map units for OM on many Midwestern silt and silty clay loam soils is ~2-3 %, the CEC range is ~5-10 (meq $100g^{-1}$), for pH a ~1-2 point range. Using proximal soil sensors, the average RMSE for the project fields for OM was 0.27, CEC 2.12, and pH 0.38. As a result, confidence intervals using sensor data are significantly lower than the soil property ranges found in the soil surveys for these fields. Slope information in soil surveys is also a coarser than measurements acquired using high-grade GPS receivers. GPS data can also be used to generate precise maps of field curvature. These advancements in relevant soil property resolution provided by the multi-sensor system are a quantifiable improvement over the information found in the accompanying soil surveys.

Soil survey inclusions can present a serious problem if inputs are varied according to the expected productivity within a map unit. Even for a 1 ha inclusion, the minimum for a fine-scale survey, the included soil represents a ~100 m $\times$ 100 m area. A large 24 row planter would make at least five passes through that inclusion, potentially metering a severely sub-optimal rate for the inclusion. Proximal soil sensors are typically operated on 15-20 m transects, which more closely matches the capability of farm equipment to apply inputs site-specifically. With GPS and proximal soil sensors the location of changes in soil properties can easily be mapped within 1-2 m. Sensor maps reflect the spatial pattern of soil as a continuum, identifying soil transitions precisely whether they occur gradually or suddenly, while soil survey lines can only depict soil differences as abrupt boundaries.

Using IL1 shown in Figure 7 as an example of the improved mapping that proximal sensors can provide, it is apparent that while the soil survey is effective at delineating the sandy soil in the 88B Sparta, it allows several sizeable inclusions in the highly productive 125 Selma clay loam and 447 Canisteo loam. The soil survey lists the OM range for Selma at 4-6 % and the Canisteo at 4-8 %. Calibrated proximal sensors mapped OM areas of <1 % included within the both of these soil types. These deviations from the survey-listed OM and CEC could seriously affect the performance of practices such as variable rate corn population and nitrogen in these survey units.

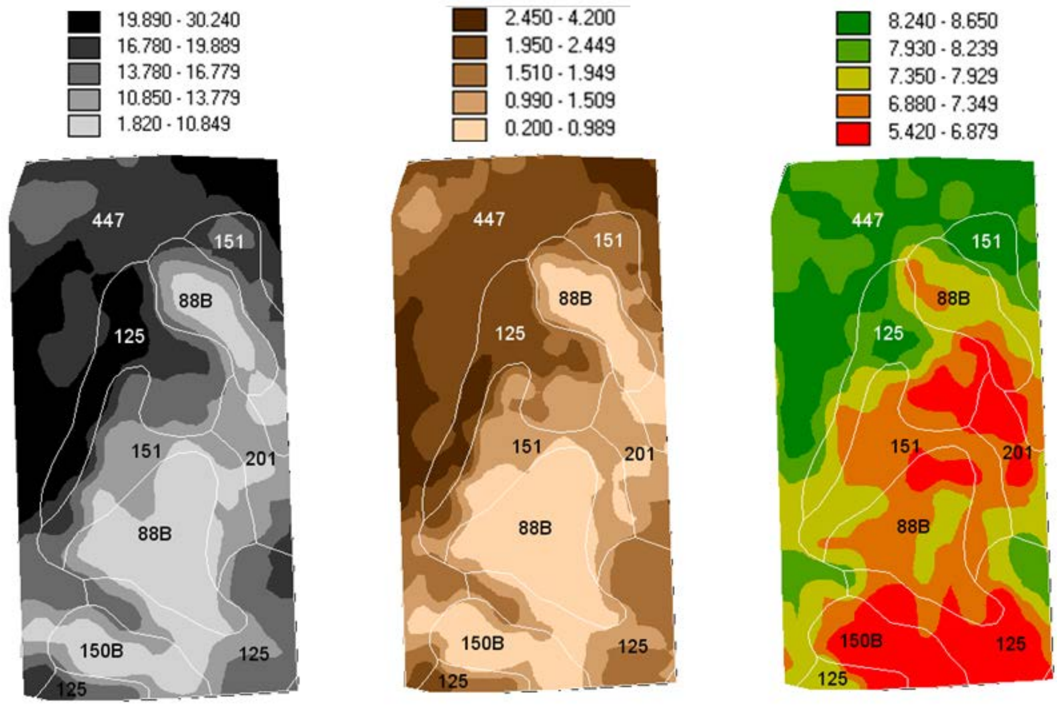

Fig. 7. Calibrated soil CEC, OM and pH maps from the proximal soil sensing systems with a USDA soil survey map overlaid for IL1.

CONCLUSIONS

This eight-field study across four Midwestern states provided an opportunity to evaluate a proximal multi-sensor platform in a variety of soil types and field conditions. Proximal soil sensor measurements correlated well with lab-analyzed soil samples, and sensor maps showed small-scale variability not detected at conventional grid sample scales or with USDA soil surveys. This is a promising development for improving the effectiveness of several variable-rate inputs. The value of the additional precision will depend on many factors including cost of inputs and value of crops grown. In order to further quantify the differences between the sensor maps and other available information, additional research is needed, using yield data, intensive soil sampling, and variable rate trials.

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REFERENCES

Adamchuk, V.I., J.W. Hummel, M.T. Morgan, S.K. Upadhyaya. 2004. On-the-go soil sensors for precision agriculture. Comput. Electron. Agric. 44:71–91.

Adamchuk, V.I., E.D. Lund, B. Sethuramasamyraja, M.T. Morgan, A. Dobermann, D.B. Marx. 2005. Direct measurement of soil chemical properties on-the-go using ion-selective electrodes. Comput. Electron. Agric. 48(3):272–294.

Bauer, A., and A.L. Black. 1994. Quantification of the effect of soil organic matter content on soil productivity. Soil Sci. Soc. of Am. J. 58:185–193.

Bianchini, A.A. and A.P. Mallarino. 2002. Soil-sampling alternatives and variable-rate liming for a soybean–corn rotation. Agron. J. 94(6):1355–1366.

Bot, A. and J. Benites. 2005. The importance of soil organic matter. Food and Agriculture Organization of the United Nations.

Brevik, E.C., T.E. Fenton, and D.B. Jaynes. 2003. Evaluation of the accuracy of a central Iowa soil survey and implications for precision soil management. Prec. Ag. 4(3):331–342.

Brouder, S.M., B.S. Hofmann, and D.K. Morris 2005. Mapping soil pH: Accuracy of common soil sampling strategies and estimation techniques. Soil Sci. Soc. of Am. J. 69:427–441.

Chang, C.W., D.A. Laird, M.J. Mausbach, and C.R. Hurburgh, Jr. 2001. Near-infrared reflectance spectroscopy – principal components regression analysis of soil properties. Soil Sci. Soc. of Am. J. 65:480–490.

Christy, C.D. 2008. Real-time measurement of soil attributes using on-the-go near infrared reflectance spectroscopy. Comput. Electron. Agric. 61(1):10–19.

Fleming, K.L., D.F. Heermann, and D.G. Westfall. 2004. Evaluating soil color with farmer input and apparent soil electrical conductivity for management zone delineation. Agron. J. 96:1581–1587.

Grisso, R., M. Alley, D. Holshouser, and W. Thomason. 2009. Precision farming tools: Soil electrical conductivity. Virginia Cooperative Extenstion. http://pubs.ext.vt.edu/442/442-508/442-508.html

Hummel, J.W., K.A. Sudduth, and S.E. Hollinger. 2001. Soil moisture and organic matter prediction of surface and subsurface soils using an NIR soil sensor. Comput. Electron. Agric. 32:49–165.

Kitchen, N.R., S.T. Drummond, E.D. Lund, K.A. Sudduth, G.W. Buchleiter. 2003. Soil electrical conductivity and other soil and landscape properties related to yield for three contrasting soil and crop systems. Agron. J. 95:483–495.

Kweon, G., C.R. Maxton, E.D. Lund. 2012. Soil organic matter sensing with an on-the-go soil optical sensor. Biosys. Eng. (submitted).

Lee, K.S., D.H. Lee, K.A. Sudduth, S.O. Chung, N.R. Kitchen, and S.T. Drummond. 2009. Wavelength identification and diffuse reflectance estimation for surface and profile soil properties. Trans. ASABE 52:683–695.

Logsdon, S., D. Clay, D. Moore, T. Tsegaye. 2008. Soil science step-by-step field analysis. P. 147. SSSA, Madison, WI.

Lund, E.D., C.D. Christy, C.D., P.E. Drummond. 1998. Applying soil electrical conductivity technology to precision agriculture. Proceedings of the 4th International Conference on Precision Agriculture, St. Paul, MN. 19–22 July.

Lund, E.D. and C.R. Maxton. 2011. Proximal sensing of soil organic matter using the Veris® OpticMapper™. The 2nd Global Workshop on Proximal Soil Sensing, McGill University, Quebec, Canada. 15–19 May.

McBratney, A., and M. Pringle. 1997. Spatial variability in soil–implications for precision agriculture. European Conference on Precision Agriculture 1. Warwick University, UK. p. 3–31.

Moore, I.D., A. Lewis, and J.C. Gallant. 1993. Terrain attributes: Estimation methods and scale effects. *In* A.J. Jakeman et al., (ed.), Modelling change in environmental systems. John Wiley and Sons Ltd, London. p. 189–214.

Natural Resources Conservation Service. 2001. Soil survey of Champaign County, Illinois. Part II. P. 268.

Soil Survey Division Staff. 1993. Soil survey manual. Soil Conservation Service, U.S. Department of Agriculture.

Surfer. 2002. User's guide. Golden software, Inc. p. 419.

Williams, B.G., and D. Hoey, 1987. The use of electromagnetic induction to detect the spatial variability of the salt and clay content of soils. Aust. J. Soil Res. 25:21–27.