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Soil organic matter and cation-exchange capacity sensing with on-the-go electrical conductivity and optical sensors

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ABSTRACT

An on-the-go optical soil sensor with 660 nm red and 940 nm near-infrared wavelengths with an electrical conductivity (EC) sensing unit were tested to estimate soil organic matter (SOM) and cation-exchange capacity (CEC) on 551 ha on 15 fields in 6 U.S. states. For calibration between sensed data and lab-analyzed values, a multivariate linear regression (MLR) with leave-one-out cross validation was performed on fields with more than 10 lab samples and a single variable linear regression was performed on fields with less than 10 samples. From the SOM calibration results, 12 of 15 fields had good results with R^2 of 0.80 or higher and RPD (Ratio of Prediction to Deviation = standard deviation / root mean square error of prediction) of 2.33 or greater. For CEC calibrations, six of nine fields had good results with R^2 of 0.86 or higher and RPD of 2.78 or greater. The best calibration model was applied to each field and the estimated SOM and CEC maps exhibited strong spatial structure and high correlation to lab-analyzed SOM in all fields. EC and optical data in each field was normalized and combined together by state and tested with MLR. Combining fields in this manner showed good results with R^2 of 0.80 or higher and RPD of 2.30 or greater for SOM in four of five states, and combined fields in two of three states showed good correlations to lab data with R^2 of 0.86 or higher and RPD of 2.69 or greater for CEC. From these results, SOM and CEC mapping with soil EC and optical sensors seems to be a promising approach. Future research will be implemented to estimate SOM and CEC more precisely by developing a reliable universal calibration model using soil EC, optical data, soil moisture contents and topographic attributes for global areas.

1. Introduction

Through variable rate technology (VRT) application, site-specific crop management (SSCM) has potential to increase profit and decrease environmental impact (Adamchuk et al., 2004; Fraisse et al., 2001; Plant, 2001). For SSCM, information about the variability of different soil attributes within a field is necessary. However traditional soil sampling is expensive and laborious, and grid sampling is not dense enough to obtain an accurate map (Bianchini and Mallarino, 2002; Lauzon, et al., 2005). Therefore various on-the-go soil sensing systems have been developed to provide high-density measurements and full field coverage at a relatively low cost (Dhillon et al., 2010).

Bauer and Black (1994) reported that soil organic matter (SOM) is an important factor in crop growth, as it affects soil moisture infiltration and retention, soil tilth, rooting depth, soil-applied herbicide activity, nitrogen release, and other aspects of nutrient cycling. A precise SOM map can provide an important piece of information for growers as they seek to vary nitrogen, seed population, herbicides, and other inputs.

Variations in soil properties can be detected, even with the human eye, based on differences in light reflectance. Darker soils contain higher levels of moisture or SOM than light-coloured soils (Alexander, 1969; Krishnan et al., 1980; Page, 1974). While this can be detected visually, light sensors in the visible and near infrared (VIS-NIR) can quantify the reflectance characteristics and provide the data needed to develop calibrations to soil properties. Soil reflectance has been studied extensively since the 1970s and is widely reported in the scientific literature as an effective means for approximating SOM (Smith et al., 1987; Stoner and Baumgardner, 1981; Sudduth and Hummel, 1993; Sudduth and Hummel, 1996).

Griffis (1985) designed an inexpensive soil organic matter sensor with an infrared light emitting diode (LED) and a phototransistor. Shonk et al. (1991) also developed a shank-mounted real-time soil organic matter sensor with a red LED (660 nm) and a photodiode, and it showed promising results, when a wide range of SOM levels were present and conditions were closely controlled.

Shibusawa et al. (1999) developed a real-time portable spectrophotometer with 400 to 2400 nm ranges that is capable of field mapping of soil properties, and showed high correlation with SOM contents as R^2 of 0.87. A commercialized VIS-NIR spectrophotometer system has been used for measurement of various soil properties such as soil organic matter, soil total carbon, soil nitrogen (Bricklemyer and Brown, 2010; Christy, 2008; Huang et al., 2007; Kweon et al., 2009).

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A VIS-NIR spectrometer was used to predict cation exchange capacity (CEC) in addition to SOM from its soil spectral response (Adamchuk et al., 2004). Since a soil's CEC is related to percent of the clay and organic matter, it can be estimated from soil texture and colour (Mengel, 1993). As the percent of clay and organic matter increases, the CEC also increases. Sudduth and Hummel (1993) reported the best CEC calibration yielded a standard error of prediction of 3.59 meq 100 g^{-1} from 30 Illinois soil samples with mean of 24.65 and standard deviation (SD) of 9.43 meq l00 g^{-1} with a portable NIR spectrophotometer. La et al. (2008) tested 37 soils, 17 from Illinois and 20 from Missouri, with mean of 13.2 and SD of 5.5 meq l00 g^{-1} using a VIS-NIR spectrometer with a range between 350 and 2500 nm. From the calibration, R^2 of 0.83, root mean square error of prediction (RMSEP) of 2.23, and RPD (Ratio of Prediction to Deviation = SD/RMSEP) of 2.45 were obtained. Lee et al. (2009) also reported CEC estimations with R^2 of 0.83, RMSEP of 3.43, and RPD of 2.47 from 165 samples from Missouri, Illinois, Michigan, South Dakota, and Iowa using the same spectrometer. 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; Williams and Hoey, 1987). 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 level indicates a more accurate prediction.

The level of technology inherent in a spectrophotometer may be appropriate for soil research to measure numerous soil properties, but are likely impractical for grower and consultant use due to expense and complexity. Veris Technologies has developed a commercially available dual-wavelength on-the go soil optical sensor (OpticMapper™) for SOM and CEC measurements with high-density and full field coverage at a relatively low cost. Kweon and Maxton (in review) found a strong correlation with R^2 of 0.87 between estimated SOM by OpticMapper and lab-analyzed SOM for 56 samples in Kansas fields. However further field tests are needed to confirm the sensor's performance for SOM and CEC estimations over different types of soils in other states.

The objectives of this study were to evaluate the performance of OpticMapper for SOM and CEC measurements on fields with various soils types and wider ranges of soil properties, and to compare SOM and CEC estimations by each field model, each combined field model by state, and a universal calibration model.

2. Materials and methods

2.1. Research sites

This study covered 551 ha on 15 fields in 6 U.S. states, providing a wide range of soil types, conditions, and organic matter levels. Soil types and textures ranged from sands in Michigan to a range of silt loams in Iowa, Illinois, Ohio, and Missouri and sandy loam in Alabama. The 15 fields are included in 10 different "major land resource areas" (MLRAs) such as sand mountain and coastal plain for Alabama, loess and drift for Illinois and Iowa, drift plain for Michigan, and till plain for Missouri and Ohio (Table 1). From these fields, 130 geo-referenced soil samples were collected for organic matter and CEC analysis. The samples were a composite of a minimum of six 0–15 cm deep cores collected within a 5 m radius, and tested in the soil testing Lab of Kansas State University and the Midwest soil testing Lab in Nebraska. Soil organic matter was measured by the Walkley–Black method (Combs and Nathan, 1998) and CEC was determined by the cation summation method with an ammonium acetate solution at a pH of 7.0 (Warncke and Brown, 1998).

2.2. On-the-go electrical conductivity and optical sensors

Soil electrical conductivity (EC) and optical data were collected with an implement designed and commercialized for the purpose of mapping with multiple soil sensors (Figure 1). The sensor modules consist of six coulter electrodes for EC measurements, and a specially configured row unit for optical measurements. The EC module identifies soil variability by directly sensing EC. As the module is pulled

Table 1
Description of the research fields in 6 states.

State	Field name	Location: county	Area (ha)	Major land resource area (MLRA)	Soil series	Soil classification
Alabama	AL1	Lawrence	30	129 Sand mountain	Decatur	Fine, kaolinitic, thermic Rhodic Paleudults
					Tyler	Fine-silty, mixed, mesic Aeric Fragiaquults
	AL2	Henry	21	133A Southern coastal plain	Dothan	Fine-loamy, kaolinitic, thermic Plinthic Kandiudults
					Lucy	Loamy, kaolinitic, thermic Arenic Kandiudults
Illinois	IL1	De Witt	132	108A IL and IA deep loess and drift	Sable	Fine-silty, mixed, mesic Typic Endoaquolls
					Buckhart	Fine-silty, mixed, mesic Oxyaquic Argiudolls
	IL2	Pike	47	115C Central MS valley wooded slopes	Beaucoup	Fine-silty, mixed, mesic Fluvaquentic Endoaquolls
					Titus	Fine, smectitic, mesic Vertic Endoaquolls
	IL3	Greene	39	115C Central MS valley wooded slopes	La Hogue	Fine-loamy, mixed, mesic Aquic Argiudolls
					Titus	Fine, smectitic, mesic Vertic Endoaquolls
Iowa	IA1	Guthrie	39	108D IL and IA deep loess and drift	Nevin	Fine-silty, mixed mesic Aquic Pachic Argiudolls
					Zook	Fine, smectitic, mesic Cumulic Vertic Endoaquolls
	IA2	Harrison	17	107B IA and MO deep loess hills	Ida	Fine-silty, mixed, mesic Typic Udorthents
					Napier	Fine-silty, mixed, mesic Cumulic Hapludolls
	IA3	Harrison	11	107B IA and MO deep loess hills	McPaul	Coarse-silty, mixed, mesic Mollic Udifluvents
					Colo	Fine-silty, mixed, mesic Cumulic Endoaquolls
Michigan	MI1	Muskegon	61	98 Southern MI and Northern IN drift plain	Au Gres	Sandy, mixed, frigid Typic Endoaquods
					Saugatuck	Sandy, mixed, mesic Typic Duraquods
Missouri	MO1	Carroll	34	109 IA and MO Heavy till plain	Leta	Clayey over loamy, smectitic, mesic Fluvaquentic Hapludolls
					Haynie	Coarse-silty, mixed, mesic Mollic Udifluvents
	MO2	Carroll	14	109 IA and MO Heavy till plain	Haynie	Coarse-silty, mixed, mesic Mollic Udifluvents
					Leta	Clayey over loamy, smectitic, mesic Fluvaquentic Hapludolls
	MO3	Lafayette	42	107B IA and MO Deep loess hills	Marshall	Fine-silty, mixed, mesic Typic Hapludolls
					Blackoar	Fine-silty, mixed, mesic Fluvaquentic Endoaquolls
Ohio	OH1	Clark	17	111A IN and OH Till plain	Kokomo	Fine, mixed, mesic Typic Argiaquolls
					Strawn	Fine-loamy, mixed, mesic Typic Hapludalfs
	OH2	Champaign	15	111A IN and OH Till plain	Kendallville Crosby	Fine-loamy, mixed, mesic Typic Hapludalfs
						Fine, mixed, mesic Aeric Epiaqualfs
	OH3	Champaign	32	111A IN and OH Till plain	Homer	Fine-loamy over sandy, mixed, mesic Aeric Endoaqualfs
					Lippincott	Fine, mixed, mesic Typic Argiaquolls

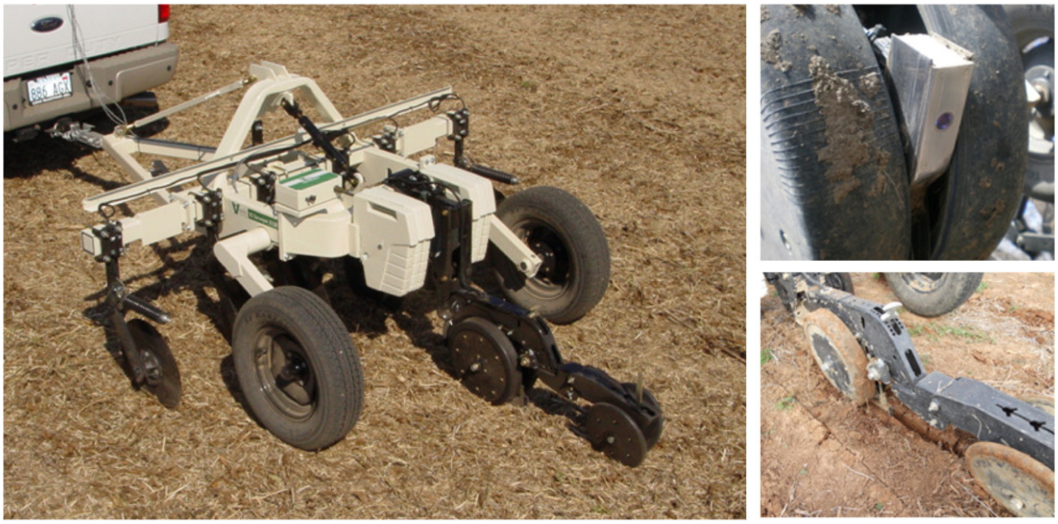

Fig. 1. Veris OpticMapper with soil EC and optical sensors.

through the field, a pair of coulter electrodes injects an electrical current into the soil, while the other coulter electrodes measure the voltage change, one pair for a “shallow” EC reading (0–30 cm) and one pair for a “deep” EC reading (0–90 cm). The EC of soils varies depending on soil particle size and the amount of moisture held by soil particles. Sands have a low conductivity, silts have a medium conductivity, and clays have a high conductivity. Consequently, EC correlates strongly to soil particle size and texture in non-saline soils (Williams and Hoey, 1987).

An optical module consists of two light sources with a red LED of 660 nm wavelength and a NIR LED of 940 nm wavelength, and a single photodiode. The module is mounted between two disks which operate at a slight angle, forming a V-shaped slot in the soil. A depth-gauging side wheel for each disk controls sensing depth. A wear plate with a sapphire window is pressed against the bottom of the slot and the consistent pressure provides a self-cleaning function. Data was collected approximately 4 cm below the soil surface at a 1 Hz rate on 15–20 m transects with speed of 10–15 km/hr. Approximately 150–200 EC and optical data points per hectare were collected (Kweon and Maxton, in review).

2.3. Data analysis

The raw data obtained by the on-the-go soil optical sensor required data processing to remove outliers. GPS outliers which are out of 100 m radius from the previous sensing location, system outliers which are out of normal ranges of soil reflectance, global field outliers that are not within three times the standard deviation from the mean of all field data, and local field outliers which are greater than two times the standard deviation from the mean at the neighboring 10 sensing points were removed in the manner described by Kweon and Maxton (in review).

To estimate SOM and CEC in fields, a calibration routine was programmed by LabVIEW (National Instruments Corp., Austin, TX, USA). The relationship between light reflectance and organic matter content for the soil with less than 5% SOM was found to be linear from previous studies (Kweon and Maxton, in review; Shonk et al., 1991). The fields in six states had mostly less than 5% SOM; therefore linear regressions were selected for calibration to estimate SOM in each field. For the calibration, each red and NIR reflectance reading and optical reading ratio (NIR/red), shallow EC (EC_SH) and deep EC (EC_DP) values and EC ratio (EC_DP/EC_SH), slope, curvature and elevation were used as independent variables. The calibration routine with multiple linear regression (MLR) tested every combination for their relationship to organic matter for each field 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 independent variable and lab-analyzed OM values.

A validation step is required to assess the calibration model for predicting data accurately without overfitting, and this procedure is generally done either by splitting the dataset randomly into independent calibration and validation sets or through a cross validation (Lee et al., 2009). In this study the number of soil samples in each field is too few for the independent validation approach, thus a leave-one-out cross validation procedure was chosen as the same manner by Christy (2008) in the previous research. A leave-one-out cross validation method leaves one sample out at a time and then uses the other samples to predict the value of the omitted sample. The process is repeated until all samples have been omitted and predicted. A new regression equation is calculated each time that does not include the influence of the left-out sample.

This leave-one-out cross validation method was applied to all possible combinations among independent variables to estimate SOM for each field, and the one with the lowest root mean square error (RMSECV) was selected for the best calibration model for the field (Kweon, 2012). Error statistics (i.e., R^2, RMSEP and RPD) for each field were calculated based on the predicted values of each best calibration model and then the model was applied to the field data to produce an SOM map. The equal number of classes was set to low, medium and high for estimated SOM maps. CEC estimations were also performed in the same manner.

To test multiple linear regressions for fields with less than 10 samples, each field was combined together by state. The best calibration model for each combined state field was created in the same manner as mentioned above with the lowest RMSECV. The soil sensor values are affected by soil temperature and moisture, thus each field may have different sensor data ranges, even if the fields have very similar soil properties. In this study, soil optical and EC data were normalized by dividing by the mean value in each field before merging data. However, the other variables were spatial data with absolute values and they did not need to be normalized.

The fields in three adjacent states of Iowa, Illinois and Missouri had similar soil properties with loam, silt and/or clay as seen in Table 1 and are located in the same Land Resource Region (LRR) as Central feed grains and livestock region, thus a universal calibration model could be attempted for the fields. The number of soil samples from all three states was too large to create a reliable calibration model due to duplicated lab values, thus half of the total samples were randomly selected for development of a universal calibration model for SOM and CEC. The best universal calibration model for each OM and CEC was created in the same manner as mentioned above with the lowest RMSECV. The universal calibration model was applied to each field in Iowa, Illinois and Missouri, and the estimated SOM and CEC values were compared with ones generated by an individual field-based calibration model and each combined field model by state.

3. Results and discussion

Descriptive statistics of soil organic matter and CEC lab values for the research fields are shown in Table 2. As expected in Table 1 with various MLRAs, there was a wide variation in the soil properties for the study fields in 6 states. Illinois, Iowa, Michigan and Ohio fields had relatively high values with wide ranges for SOM; especially OH3 which had 1.4–6.9% SOM. Alabama and Missouri fields had relatively low values with narrow ranges for SOM; for example, MO3 had only a range of 1.6–2.4% of SOM. CEC also varied considerably across the research fields from very low and narrow range value for AL2 (2.2–3.5 meq 100 g^{-1}) to high and wide value for MO1 (14.6–32.9 meq 100 g^{-1}). Missouri fields had wider range of CEC than SOM, and Alabama and Michigan had low and narrow ranged CEC. This might be due to different soil types as seen in Table 1. Mengel (1993) reported light colored sands has only 3–5 meq 100 g^{-1} of CEC, and dark colored silty clay loams and silty clays has 30–40 meq 100 g^{-1} of CEC for common color and texture soil groups. Illinois and Ohio fields did not have lab analyzed CEC values in this study.

Table 3 shows descriptive statistics of optical readings for red and NIR reflectance for the research fields in 6 states. Alabama fields showed low reflectance in both red and NIR and Ohio fields showed high optical reflectance readings. Mostly darker soils have less reflection; however this case was because of different soil conditions when they were mapped. Fields AL2 and IA1 had different SOM ranges but showed very similar NIR readings. Fields IL1 and IA1 had similar SOM contents, but showed different optical readings. This is likely due to different field moisture levels at mapping. AL2 and IA1 fields may have been mapped under high moisture conditions, or IL1field was mapped under dry soil conditions. According to the research by Kweon and Maxton (in review), 10% of moisture increase in soil samples caused over 43 in red and 100 in NIR reflectance reading decrease in the lab test. Because moisture is the most significant factor in addition to soil organic matter contents for soil reflectance measurement with a dual-wavelength optical sensor, moisture variation should be considered when field data are combined for calibration, or when data from multiple fields are calibrated by one universal model. In this research, normalization was used for each dataset since the soil moisture contents were not obtained for the calibrations for combined fields or by a universal model. A moisture sensor along with optical sensor would have benefit for more precise SOM mapping.

The correlation between red and NIR reflectance for the study fields showed mostly high with R^2 of 0.68–0.95 except in AL1 having the lowest R^2 of 0.24. However another field in Alabama, AL2, had the highest R^2 of 0.95 between red and NIR. The reason may be because the two fields had different soil types and are located in different MLRA, although both AL1 and AL2 were mapped around the same time and showed similar ranged optical reflectance. Fig. 2 shows the relationships between red and NIR reflectance readings for each field in six states.

Table 4 shows selected variables for SOM calibrations and the results for the research fields in 6 states. From the table, 12 of 15 fields had good results with R^2 of 0.80 or higher and RPD of 2.33 or greater. AL2 had the lowest R^2 and RPD with 0.37 and 1.46, respectively. This low correlation may be due to low variability in soil samples as shown in Table 2. Among the fields with more than 10 samples, AL1, IL1 and MI1 used only two variables for MLR, but all MO fields used more than three variables for MLR. Particularly, MO2 used 8 variables for MLR to obtain the lowest RMSECV. This result was because of no dominant variable for SOM calibration in the field. Optical data were selected in nine fields, and EC data were chosen in 10 fields for SOM calibrations. However, optical ratio was not used in any field. Topographic data were used in four fields including slope selected in three fields, curvature in two fields and elevation in one field. Correlations between SOM and the variables used for calibrations would be shown later in this section.

In order to investigate how topography affects OM calibration, ten best calibration results are shown in Table 5 by ascending order for RMSECV for IL1 field. Six calibrations used topographic data including curvature selected in 4 models. Shallow EC with curvature showed 0.04 lower RMSECV than shallow EC alone, but slope and elevation did not help to improve RMSECV in the calibration with shallow EC. In IL1 field, EC data are dominant over optical and topographic data for SOM calibrations.

With the ten best models, it was found that the optimal number of variables used in each calibration is typically only one or two. From the above results, the calibration with a leave-one-out validation method seems to be a proper approach for MLR over the concern of overfit.

Fig. 3 shows lab-analyzed values overlaid on estimated SOM maps for each representative field in the six states. Sensor-estimated SOM maps exhibit strong spatial structure and visual correlation to lab-analyzed SOM in all fields. Especially, MO1 with 31 dense soil

Table 2
Descriptive statistics of soil organic matter (SOM) and cation exchange capacity (CEC) lab values for the research fields in 6 states.

State	Field	No. of samples	SOM (%)			CEC (meq 100 g^{-1})		
			Mean	Range	SD	Mean	Range	SD
Alabama	AL1	10	1.82	1.1–3.5	0.76	8.17	5.1–13.6	2.66
	AL2	4	1.28	0.9–2.0	0.50	2.80	2.2–3.5	0.54
Illinois	IL1	10	3.82	3.0–5.1	0.78	–	–	–
	IL2	5	1.78	1.2–2.3	0.47	–	–	–
	IL3	5	1.30	0.4–2.7	0.86	–	–	–
Iowa	IA1	6	3.87	2.6–5.3	0.94	20.13	17.6–22.4	1.70
	IA2	6	2.40	1.5–2.7	0.45	18.62	16.4–21.9	2.22
	IA3	4	2.58	1.7–3.7	0.83	18.23	14.4–23.3	3.90
Michigan	MI1	11	2.97	1.7–4.5	0.92	7.66	5.8–10.1	1.40
Missouri	MO1	31	2.60	1.5–3.4	0.51	24.00	14.6–32.9	4.86
	MO2	13	1.82	1.0–2.4	0.46	18.46	10.6–22.4	3.60
	MO3	12	2.04	1.6–2.4	0.28	14.70	12.0–17.8	1.78
Ohio	OH1	5	2.74	1.5–3.8	0.98	–	–	–
	OH2	4	2.13	1.3–2.9	0.90	–	–	–
	OH3	4	3.48	1.4–6.9	2.57	–	–	–

Table 3
Descriptive statistics of optical readings for the research fields in 6 states.

State	Field	Red reflectance			NIR reflectance			R^2 between Red and NIR
		Mean	Range	SD	Mean	Range	SD	
Alabama	AL1	82.00	65–101	5.66	261.3	203–323	19.20	0.24
	AL2	81.91	63–112	6.61	256.2	191–350	23.15	0.95
Illinois	IL1	115.8	92–150	9.35	333.2	246–444	31.11	0.83
	IL2	116.9	96–142	7.31	328.8	265–401	22.49	0.81
	IL3	139.2	108–182	14.19	395.9	275–512	44.64	0.89
Iowa	IA1	92.7	85–113	3.88	249.0	205–313	15.38	0.78
	IA2	126.2	109–159	6.99	403.5	342–488	24.41	0.80
	IA3	117.1	106–147	4.96	379.6	333–437	17.95	0.88
Michigan	MI1	115.4	103–135	5.50	306.2	241–372	20.17	0.84
Missouri	MO1	120.9	105–150	6.90	306.2	252–390	21.71	0.68
	MO2	127.9	106–159	10.19	338.6	266–427	29.79	0.91
	MO3	124.2	108–153	6.80	340.3	274–422	22.84	0.82
Ohio	OH1	172.5	133–216	14.47	319.1	278–362	9.66	0.82
	OH2	169.6	130–221	9.84	282.1	233–335	10.06	0.76
	OH3	173.0	104–268	12.91	304.3	240–420	14.78	0.73

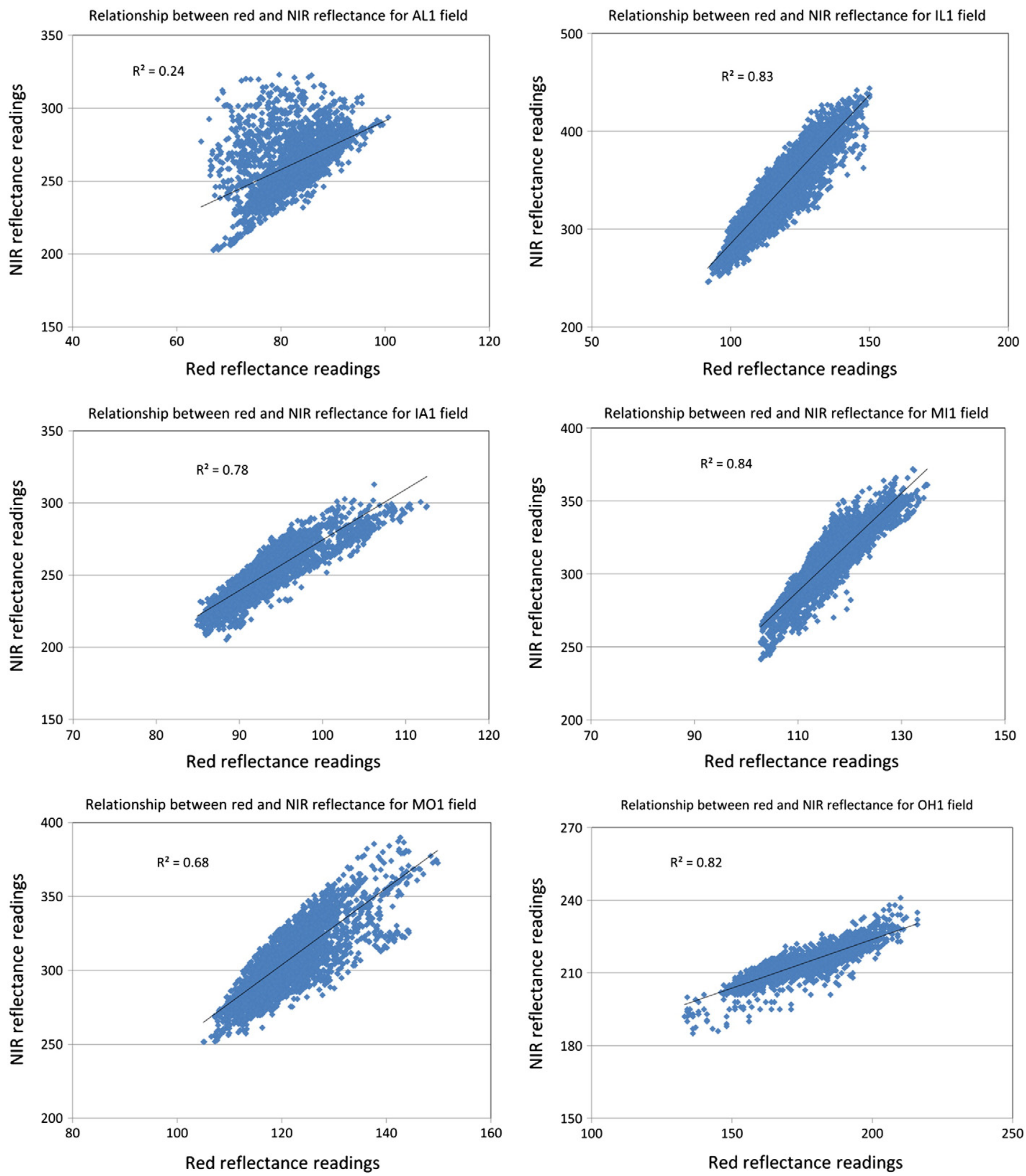

Fig. 2. Relationships between red and NIR reflectance readings for representative fields in six states.

samples shows good correlation between lab data and estimated SOM. The spatial structure of SOM in each field is discernible even without interpolating or other manipulation.

Table 6 shows selected variables for CEC calibrations and the results for the research fields in 4 states. From the table, six of nine fields had good results with R^2 of 0.86 or higher and RPD of 2.78 or greater. IA2 showed the lowest calibration result with R^2 of 0.40 and RPD of 1.41, and this field did not show good result either in the SOM calibration (R^2 of 0.57 and RPD of 1.67). AL2, which had the lowest R^2 of 0.37 and RPD of 1.46 in the SOM calibration, showed very good result in CEC calibration with R^2 of 0.93 and RPD of 4.30. Among the fields with more than 10 samples, AL1 used two variables and MI1 selected only one variable for their calibrations, but three MO fields used at least five variables. The variable of shallow EC was

Table 4
Selected variables for SOM calibrations and the results for the research fields in 6 states.

State	Field	Selected variable(s)	R^2	RMSEP (%)	RMSECV (%)	RPD
Alabama	AL1	Red, EC_SH	0.81	0.31	0.48	2.43
	AL2	NIR	0.37	0.34	0.65	1.46
Illinois	IL1	EC_SH, Curvature	0.82	0.31	0.44	2.50
	IL2	EC_DP	0.92	0.12	0.17	3.98
	IL3	EC_SH	0.94	0.19	0.31	4.58
Iowa	IA1	NIR	0.92	0.24	0.37	3.91
	IA2	Red	0.57	0.27	0.53	1.67
	IA3	NIR	0.95	0.16	0.28	5.09
Michigan	MI1	NIR, EC_SH	0.92	0.25	0.33	3.54
Missouri	MO1	EC_DP, EC ratio, Slope	0.70	0.28	0.31	1.84
	MO2	Red, NIR, EC_SH, EC_DP, EC ratio, Slope, Curvature, Elevation	0.97	0.08	0.20	5.68
	MO3	Red, EC ratio, Slope	0.80	0.12	0.18	2.33
Ohio	OH1	EC_SH	0.96	0.16	0.31	5.94
	OH2	EC_SH	0.99	0.04	0.07	25.03
	OH3	Red	0.83	0.91	1.83	2.82

chosen in seven fields, and red and NIR were used for each two fields for the CEC calibrations. Topographic data were used in three MO fields as used in the SOM calibrations. Correlations between CEC and the variables would be shown later in this section.

The best calibration model was applied in each field for CEC map creation, and Fig. 4 shows the estimated SOM maps on which lab-analyzed values were overlaid. Like SOM maps in Fig. 3, sensor-estimated SOM maps show strong spatial structure and high correlation to lab-analyzed SOM in all fields. From comparison between two soil properties maps, the patterns were similar; high SOM areas typically had high CEC and low SOM areas had low CEC values. This is because a soil's CEC is related to percent of organic matter (as the percent of organic matter increases, the CEC also increases) as discussed earlier. From these results, SOM and CEC mapping with soil EC and optical sensors seems to be a promising approach.

To investigate the relationships between soil properties and soil sensor and topographic data, correlation coefficients (R) were calculated in Table 7 for the research fields. Generally, optical data is inversely correlated with SOM, and EC data is proportionally correlated with CEC. Mostly at least one sensor data had good correlation to SOM except in MO2 and MO3. The low correlation between sensor data and SOM in MO2 and MO3 may be due to low variability in soil samples as shown in Table 2 and more complex interactions between sensor data and soil properties than other fields. This situation results in selecting many variables for SOM calibration as shown in Table 4. EC data showed good correlation with SOM in IL1, IL2, IL3, OH1 and OH2; therefore EC data were selected for SOM calibrations in these fields. Optical data were highly correlated with SOM in IA1, IA3, MI1, OH1 and OH3, and the optical data were used for their calibration in except in OH1. OH1 had good correlations between SOM and both EC ($R=0.98$) and optical data ($R=-0.94$) and higher correlation with EC was selected for a calibration model. AL1 and MI1 selected both EC and optical data for SOM calibrations because the two fields had moderate correlation for SOM to both data. EC ratio was used in all Missouri fields and especially EC ratio had the highest correlation ($R=0.73$) among other sensor data in MO3. OM ratio was not selected in any field for SOM calibrations. Topographic data were not used for a primary variable, but used as a secondary variable with sensor data in IL1 and three MO fields.

Table 5
Ten best SOM calibrations results by selected variables for IL1 field.

Selected variable(s)	R^2	RMSEP (%)	RMSECV (%)	RPD
EC_SH, Curvature	0.82	0.31	0.44	2.50
EC_DP, EC ratio, Curvature	0.92	0.28	0.45	2.76
EC_SH	0.75	0.37	0.48	2.12
EC_DP, EC ratio	0.80	0.34	0.48	2.33
EC_SH, Elevation	0.75	0.37	0.48	2.13
EC_SH, Slope	0.76	0.36	0.50	2.15
EC_SH, EC_DP, EC ratio, Curvature	0.90	0.24	0.50	3.27
Red, EC_SH	0.77	0.36	0.50	2.20
EC_DP, Curvature	0.73	0.39	0.50	2.03
NIR, EC_SH	0.76	0.36	0.51	2.16

For CEC calibrations, EC was selected in AL1, AL2, IA2, IA3, MO1, MO2 and MO3 which had good or moderate correlations between CEC and EC. AL2 and IA3 showed higher than 0.96 of R for shallow EC. IA1 and MI1 had much higher correlation for CEC to optical data, thus optical data were selected for CEC calibrations. Three Missouri fields showed much higher correlation for CEC to EC data than optical data, but optical ratio, which had moderate correlation with R of $|0.63|$ or higher, helped to improve the results. Some topographic data helped for CEC calibrations such as slope which had the highest correlation ($R=|0.73|$) among other sensor data in MO2. All the best 10 CEC calibration models for MO2 included slope. However, generally the relationships between topographic and soil properties are not consistently correlated. In some fields, the correlation coefficients are weak and inverted.

Table 8 shows selected variables for SOM calibrations and the results for combined fields. All combined field models selected both EC and optical data, and a universal calibration model chose optical data and topographic data. Four combined fields of five had good results with R^2 of 0.80 or higher and RPD of 2.30 or greater except combined Missouri fields which had R^2 of 0.68 or higher and RPD of 1.79. Combined Illinois and Ohio fields showed very good correlations to SOM with R^2 of 0.94 and 0.92 and RPD of 4.27 and 3.73, respectively. These results were as good as the ones for individual fields in these states by each field-based calibration. A universal calibration model was developed and showed R^2 of 0.55 and RPD of 1.50 for SOM with the data in Iowa, Illinois and Missouri. This result is lower than each field-based model and each combined field model. Normalization is effective to reduce moisture variation for EC and optical data in the fields mapped under similar conditions with similar soil texture for a combined field calibration model; however the fields in these three states were mapped in different seasons under different conditions. This may cause important information for EC and optical readings to be lost by normalization. For example, optical readings for IA2 and MO2 are similar around 127 for red reflectance in Table 3 but SOM is different as 2.4% and 1.82% as seen in Table 2; therefore calibration after normalization for the two fields results in erroneous output. Soil moisture contents along with EC and optical data would help to obtain better calibration results for fields over different states.

Table 9 shows selected variables for CEC calibrations and the results for combined fields. All combined field models selected both EC and optical data and elevation. Combined Alabama field showed the highest R^2 and RPD of 0.92 and 3.70 for CEC calibrations, and this result was as good as the ones for individual field by each field-based calibration. Combined Missouri field showed better correlation for CEC than SOM with R^2 of 0.86 and RPD of 2.69, but combined Iowa field had lower R^2 and RPD than SOM with 0.67 and 1.80, respectively. A universal calibration model for CEC with Iowa and Missouri data did not have good correlation with R^2 of 0.52 and RPD of 1.46 as the SOM universal calibration model had. From the above findings, an each field-based calibration is feasible but it appears that combined field calibration models by state with normalization also provide acceptable estimates. Further research is needed to investigate how soil moisture values along with the sensor data improve calibration results.

Table 10 shows comparison of SOM and CEC estimations by each field model, each combined field model by state, and a universal calibration model. Estimated SOM and CEC by combined field models typically showed higher RMSEP and lower RPD than ones by each individual field model, although some fields such as AL1 and IL3 for SOM and IA2 for CEC showed better results. SOM and CEC estimations

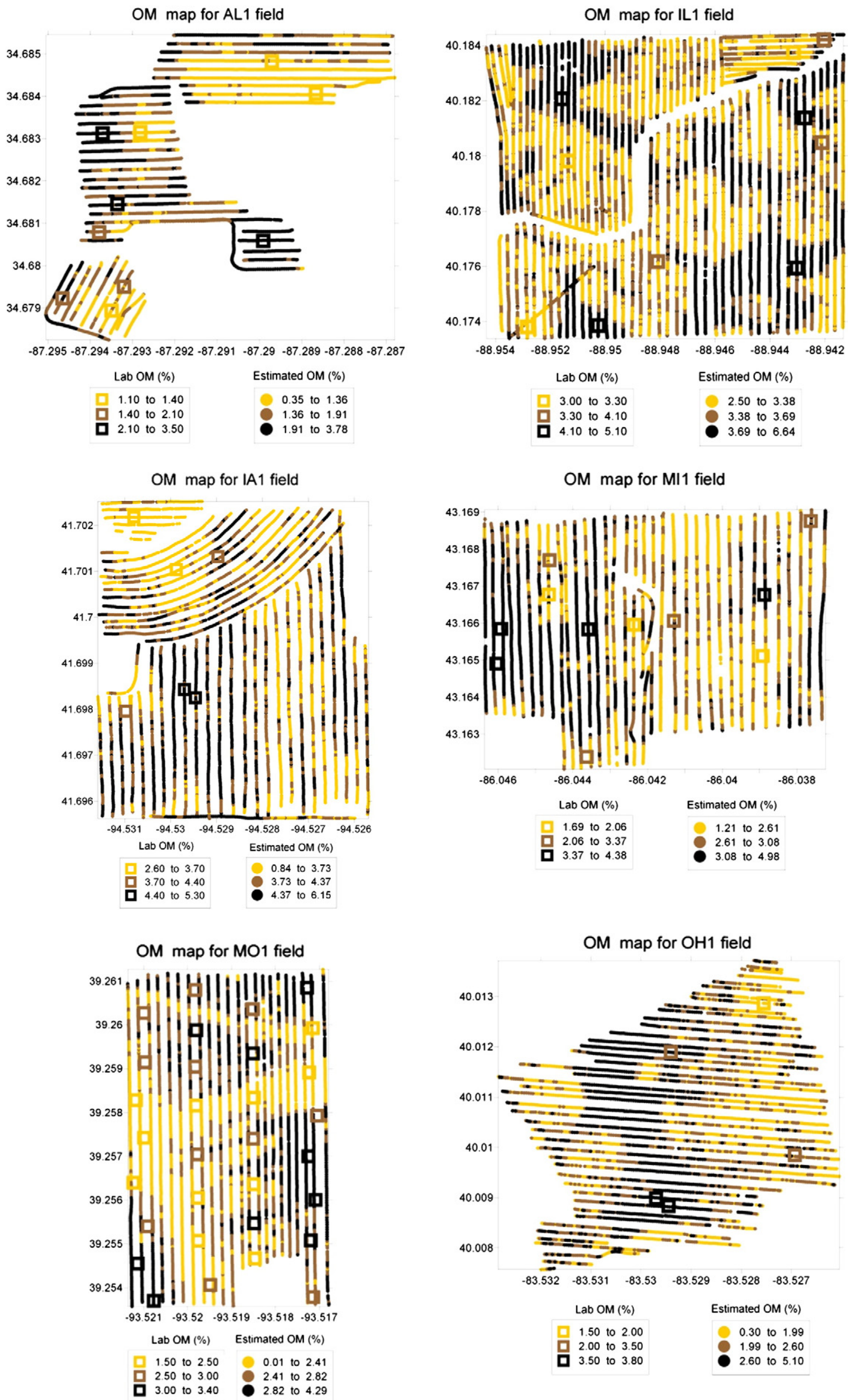

Fig. 3. Lab-analyzed values overlaid on estimated SOM maps for each representative field in six states.

Table 6
Selected variables for CEC calibrations and the results for the research fields in 4 states.

State	Field	Selected variable(s)	R^2	RMSEP (meq 100 g^{-1})	RMSECV (meq 100 g^{-1})	RPD
Alabama	AL1	Red, EC_SH	0.86	0.95	1.47	2.81
	AL2	EC_SH	0.93	0.13	0.29	4.30
Iowa	IA1	NIR	0.76	0.77	1.32	2.22
	IA2	EC_SH	0.40	1.57	2.06	1.41
	IA3	EC_SH	0.96	0.64	1.36	6.08
Michigan	MI1	NIR	0.68	0.75	0.91	1.84
Missouri	MO1	Optical ratio, EC_SH, EC_DP, EC ratio, Curvature	0.87	1.75	2.09	2.78
	MO2	Optical ratio, EC_SH, EC_DP, EC ratio, Slope, Curvature	0.96	0.72	1.37	5.03
	MO3	Red, Optical ratio, EC_SH, EC_DP, Elevation	0.93	0.46	0.88	3.85

by universal calibration model did not show good correlations to lab values except IL3 which had RPD of 4.30 for SOM.

The measured reflectance values by the optical sensor is mainly the function of soil texture, soil moisture, distance between soil surface and a sensor, and soil organic matter content (Kweon and Maxton, in review; Shonk et al., 1991). Variations due to soil texture interactions for SOM estimation can be compensated by an EC sensor, and variations caused by inconsistent distance can be removed by controlling the depth of the row unit. To remove variations due to different moisture conditions, the use of a soil moisture sensor such as

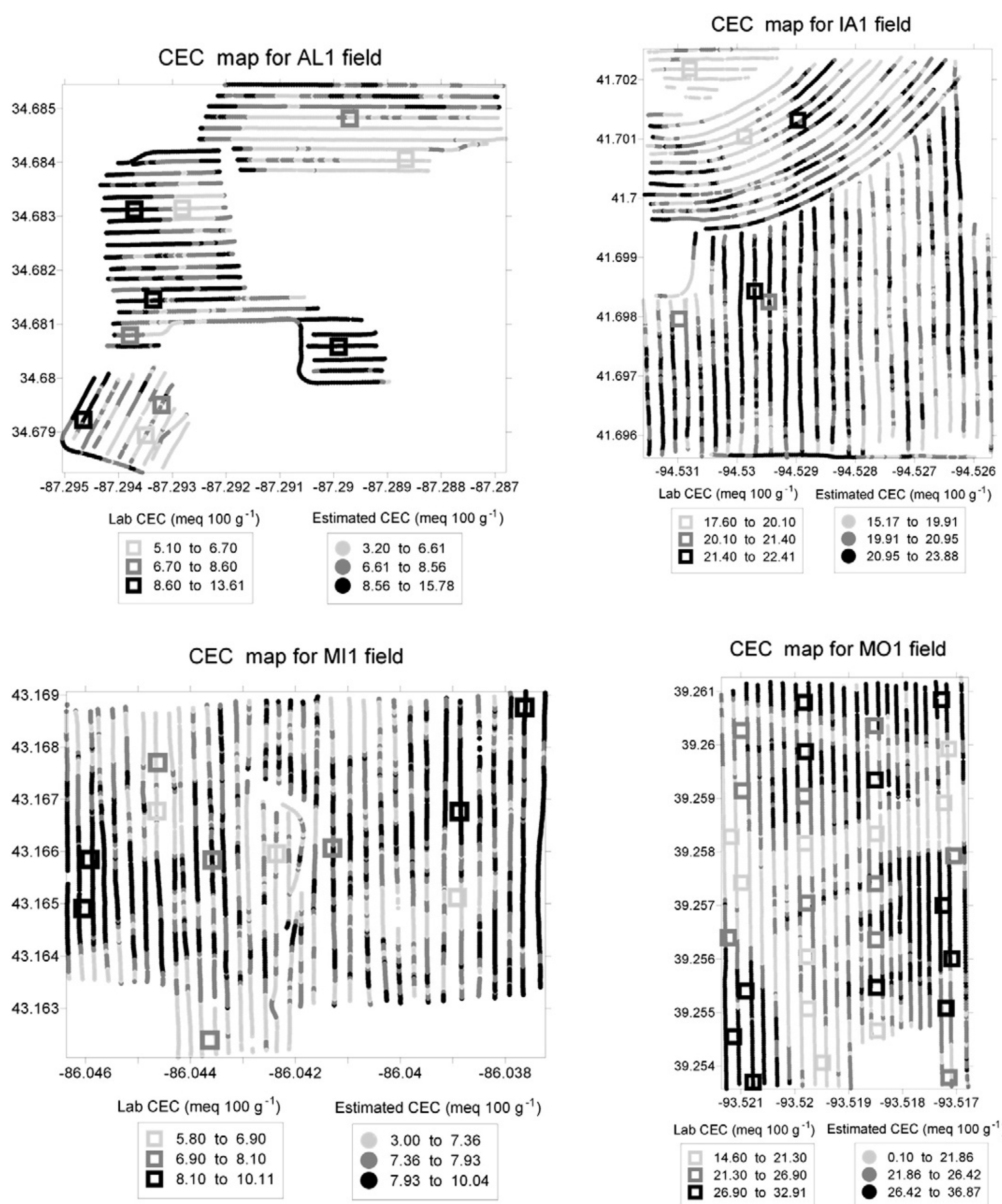

Fig. 4. Lab-analyzed values overlaid on estimated CEC maps for each representative field in four states.

Table 7
Correlation coefficients between soil properties and sensor and topographic data for the research fields.

	SOM vs.									CEC vs.								
Field	EC Sh	EC Dp	EC ratio	Red	NIR	Optc ratio	Slp	Curv	Elv	EC Sh	EC Dp	EC ratio	Red	NIR	Optc ratio	Slp	Curv	Elv
AL1	0.71	0.58	−0.30	−0.56	0.04	0.76	−0.07	0.18	0.29	0.74	0.59	−0.29	−0.56	0.07	0.79	−0.05	0.20	0.29
AL2	0.63	0.24	−0.61	−0.60	−0.61	−0.66	−0.19	−0.02	−0.53	0.96	0.77	−0.77	−0.56	−0.58	−0.73	−0.43	0.05	−0.31
IL1	0.87	0.76	−0.43	−0.75	−0.79	−0.54	−0.53	0.77	−0.68	–	–	–	–	–	–	–	–	–
IL2	0.95	0.96	−0.21	−0.83	−0.78	−0.46	−0.54	0.62	−0.78	–	–	–	–	–	–	–	–	–
IL3	0.97	0.97	−0.48	−0.56	−0.82	−0.92	−0.49	0.82	−0.85	–	–	–	–	–	–	–	–	–
IA1	−0.18	0.35	0.93	−0.92	−0.96	−0.53	−0.75	−0.47	−0.81	0.03	0.40	0.81	−0.73	−0.87	−0.81	−0.44	−0.25	−0.45
IA2	−0.65	−0.48	0.39	−0.75	−0.52	0.73	0.02	0.53	−0.27	0.63	0.57	−0.29	0.22	−0.06	−0.88	−0.12	−0.91	0.96
IA3	0.43	0.61	0.41	−0.97	−0.97	0.32	0.47	−0.42	−0.11	0.98	0.96	0.13	−0.42	−0.66	−0.57	0.61	0.47	0.73
MI1	0.75	0.60	−0.61	−0.89	−0.87	−0.54	0.03	0.51	−0.15	0.31	0.19	−0.56	−0.79	−0.82	−0.63	0.49	0.55	0.34
MO1	0.79	0.48	−0.23	0.19	−0.30	−0.65	−0.46	0.27	−0.31	0.88	0.53	−0.21	0.12	−0.44	−0.79	−0.55	0.33	−0.52
MO2	0.51	0.41	−0.33	−0.09	−0.33	−0.62	−0.77	0.52	0.06	0.62	0.44	−0.52	0.01	−0.22	−0.63	−0.73	0.39	0.14
MO3	−0.47	−0.26	0.73	−0.46	−0.28	0.40	0.04	0.35	0.18	0.49	0.64	0.46	0.01	0.04	0.07	0.36	−0.15	0.36
OH1	0.98	–	–	−0.92	−0.94	0.93	−0.69	0.75	−0.85	–	–	–	–	–	–	–	–	–
OH2	0.99	–	–	−0.78	0.29	0.97	0.64	−0.72	−0.23	–	–	–	–	–	–	–	–	–
OH3	0.19	–	–	−0.91	−0.94	0.86	0.11	0.67	0.17	–	–	–	–	–	–	–	–	–

a soil capacitance sensor or an optical sensor with strong water vapor absorbance wavelengths could be added. For development of calibration models for combined fields, it is important to consider soil type similarity for field grouping on the basis of the natural boundaries defined by the MLRAs not by man-made political boundaries (Sudduth et al., 2005).

Calibrating the sensor measurements with lab results is not merely an aspect of research and development, but is integral to commercial deployment of the OpticMapper. Typically, soil EC measurements are not calibrated to a soil test property, but are used as relative values of soil texture variability. The exception to this practice is in saline fields where bulk soil EC data can be calibrated with lab-measured salinity. Soil EC is usually not calibrated with lab data in non-saline soils for a number of reasons: the depth of EC signal penetration makes it difficult to acquire reference samples, EC signals integrate multiple soil properties, and soil texture is an expensive lab test that is not typically conducted on farm fields. Calibrating EC alone with CEC generates mixed results, as shown in Table 7. When CEC and OM are highly correlated, calibrating EC with CEC can be acceptable, but when they are independent, as in the case of high clay/low OM soils, the results are poor. The addition of the optical soil sensor represents a measurement technology that responds to optical soil properties rather than electrical properties. As a result, the combination of sensors is able to differentiate between soils with similar EC values but dissimilar CEC values. Similarly, OM calibration results using the sensor combination are stronger than from optical data alone. Further study will be implemented to validate a global calibration model with other sensor data such as moisture in addition to EC, optical and topographic data.

4. Conclusions

An on-the-go optical soil sensor with 660 nm red and 940 nm infrared wavelengths with an electrical conductivity sensing unit estimated soil organic matter contents and cation-exchange capacity on 551 ha on 15 fields in 6 U.S. states. For calibration between sensed data and lab-analyzed values, a multivariate linear regression with leave-one-out cross validation was performed on fields with more than 10 lab samples and a single variable linear regression was performed on fields with less than 10 samples. From the SOM calibration results, 12 of 15 fields had good results with R^2 of 0.80 or higher and RPD of 2.33 or greater. For CEC calibrations, six of nine fields had good results with R^2 of 0.86 or higher and RPD of 2.78 or greater. Each the best calibration models was applied to each field and the estimated SOM and CEC maps exhibited strong spatial structure and high correlation to lab-analyzed SOM in all fields.

EC and optical data in each field was normalized and combined together by state and tested with MLR. Combining fields in this manner showed good results with R^2 of 0.80 or higher and RPD of 2.30 or greater for SOM in four of five states, and combined fields in two of three states showed good correlations to lab data with R^2 of 0.86 or higher and RPD of 2.69 or greater for CEC. A universal calibration model was developed with the data from Iowa, Illinois and Missouri and showed not as high as the results of each individual field model or combined field models with R^2 of 0.55 and RPD of 1.50 for SOM and R^2 of 0.52 and RPD of 1.46 for CEC.

From the comparison of SOM and CEC estimations by each field model, each combined field model by state, and a universal calibration model, estimated SOM and CEC by combined field models and by a universal calibration model typically did not show good correlations to lab values. This poor estimation might result from the loss of the level of reflectance values for specific SOM contents due to normalization. A soil moisture sensor would help to solve this problem by considering soil moisture contents on soil reflectance values. Based on these findings, future research will be implemented to estimate SOM and CEC more precisely by developing a reliable universal calibration model using soil EC, optical data, soil moisture contents and topographic attributes for global areas.

Table 8
Selected variables for SOM calibration and the results for combined fields.

Combined field	No. of samples	Selected variable(s)	R^2	RMSEP (%)	RMSECV (%)	RPD
Alabama	14	NIR, Optical ratio, EC_SH, EC_DP	0.80	0.31	0.51	2.30
Illinois	20	NIR, EC_SH, Elevation	0.94	0.32	0.42	4.27
Iowa	16	Red, EC ratio	0.88	0.11	0.41	3.01
Missouri	56	Red, NIR, Optical ratio, EC_DP, EC ratio, Slope, Curvature, Elevation	0.68	0.32	0.39	1.79
Ohio	11	Red, EC_SH	0.92	0.27	0.36	3.73
Iowa, Illinois and Missouri[a]	46	Red, NIR, Slope, Elevation	0.55	0.77	0.87	1.50

[a] Universal calibration model for SOM.

Table 9
Selected variables for CEC calibrations and the results for combined fields.

Combined field	No. of samples	Selected variable(s)	R^2	RMSEP (meq 100 g^{-1})	RMSECV (meq 100 g^{-1})	RPD
Alabama	14	Red, NIR, EC_SH, Elevation	0.92	0.91	1.54	3.70
Iowa	16	NIR, EC_DP, Elevation	0.67	1.40	1.94	1.80
Missouri	56	Red, NIR, Optical ratio, EC_DP, EC ratio, Slope, Curvature, Elevation	0.86	2.08	2.51	2.69
Iowa & Missouri[a]	36	Optical ratio, EC_SH, Curvature, Elevation	0.52	3.61	4.25	1.46

[a] Universal calibration model for CEC.

Table 10
Comparison of SOM and CEC estimations by each field model, each combined field model by state, and a universal model.

Field	SOM (%)						CEC (meq 100 g^{-1})					
	Field model		Combined field model		Universal model		Field model		Combined field model		Universal model	
	RMSEP	RPD	RMSEP	RPD	RMSEP	RPD	RMSEP	RPD	RMSEP	RPD	RMSEP	RPD
AL1	0.31	2.43	0.28	2.67	–	–	0.95	2.81	1.00	2.67	–	–
AL2	0.34	1.46	0.38	1.32	–	–	0.13	4.30	0.65	0.83	–	–
IL1	0.31	2.50	0.41	1.91	1.24	0.63	–	–	–	–	–	–
IL2	0.12	3.98	0.23	2.05	0.34	1.38	–	–	–	–	–	–
IL3	0.19	4.58	0.17	5.18	0.20	4.39	–	–	–	–	–	–
IA1	0.24	3.91	0.66	1.44	1.17	0.80	0.77	2.22	1.40	1.21	2.19	0.78
IA2	0.27	1.67	0.48	0.94	0.88	0.51	1.57	1.41	1.33	1.67	4.58	0.49
IA3	0.16	5.09	0.49	1.69	0.96	0.86	0.64	6.08	1.50	2.61	3.03	1.29
MO1	0.28	1.84	0.30	1.72	0.42	1.22	1.75	2.78	1.89	2.58	3.28	1.48
MO2	0.08	5.68	0.30	1.54	0.74	0.62	0.72	5.03	2.14	1.68	3.24	1.11
MO3	0.12	2.33	0.38	0.72	0.51	0.54	0.46	3.85	2.47	0.72	5.19	0.34
OH1	0.16	5.94	0.44	2.22	–	–	–	–	–	–	–	–
OH2	0.04	25.03	1.14	0.78	–	–	–	–	–	–	–	–
OH3	0.91	2.82	1.95	1.32	–	–	–	–	–	–	–	–

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