THE INTERNATIONAL SOCIETY OF PRECISION AGRICULTURE PRESENTS THE
13th INTERNATIONAL CONFERENCE ON
PRECISION AGRICULTURE
July 31-August 4, 2016 • St. Louis, Missouri USA

Sensor Based Soil Health Assessment

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A paper from the Proceedings of the
13th International Conference on Precision Agriculture
July 31 – August 4, 2016
St. Louis, Missouri, USA

Abstract. *Quantification and assessment of soil health involves determining how well a soil is performing its biological, chemical, and physical functions relative to its inherent potential. Due to high cost, labor requirements, and soil disturbance, traditional laboratory analyses cannot provide high resolution soil health data. Therefore, sensor-based approaches are important to facilitate cost-effective, site-specific management for soil health. In the Central Claypan Region, visible, near-infrared (VNIR) diffuse reflectance spectroscopy has successfully been used to estimate biological components of soil health as well as Soil Management Assessment Framework (SMAF) scores. In contrast, estimation models for important chemical and physical aspects of soil health have been less successful with VNIR spectroscopy. In this study, a sensor fusion approach was investigated that incorporated VNIR spectroscopy, soil apparent electrical conductivity (*EC_a*), and penetration resistance measured by cone penetrometer (i.e., cone index, CI). Soil samples were collected from two depths (0-5 and 5-15 cm) at 108 locations within a 10-ha research site encompassing different cropping systems and landscape positions. Soil health measurements and VNIR spectral data were obtained in the laboratory, while CI and *EC_a* data were obtained in situ. Calibration models were developed with partial least squares (PLS) regression and model performance was evaluated using coefficient of determination (*R^2*), root mean squared error (RMSE), and residual prediction deviation (RPD). Models integrating *EC_a* and CI with VNIR reflectance data improved estimates of the overall SMAF score (*$R^2 = 0.78$*, RPD = 2.13) relative to VNIR alone (*$R^2 = 0.69$*, RPD = 1.82), reducing RMSE by 14%. Improved models were also achieved for estimates of the individual biological, chemical, and physical soil health scores. The results of this study illustrate the potential for rapid, in-field quantification of soil health by fusing VNIR sensors with auxiliary data obtained from complementary sensors.*

Keywords. *VNIR spectroscopy, soil health, reflectance, apparent electrical conductivity, cone index*

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Introduction

Soil health represents the nexus of multiple soil functions, such as crop productivity, environmental protection, and soil conservation (Karlen et al., 2003). Assessment and quantification of soil health currently requires measurement of multiple soil chemical, physical, and biological soil properties, referred to as soil health indicators. Measurement of these indicators often involves costly and labor-intensive laboratory analyses, which prohibits the production of spatially dense, field-scale information. In contrast, on-the-go sensor technology has the potential to provide high-resolution spatial data quickly at low cost (Hummel et al., 1996). Soil sensors have been widely used to estimate individual soil properties, and sensor fusion, as described by Adamchuk et al. (2011), has been applied to improve estimates of multiple soil attributes (e.g., Wetterlind et al., 2015). Although the ability to reliably estimate soil health indicators in the field has clear benefits for sustainable agricultural management, no single sensor has demonstrated the ability to estimate across the wide range of soil properties represented by soil health. Therefore, soil health assessment represents an ideal opportunity for the application of sensor fusion technology.

Visible, near-infrared diffuse reflectance (VNIR) spectroscopy has been used to successfully estimate several biological soil health indicators, including soil organic C, total N, β-glucosidase activity, active C, microbial biomass-C, and soil respiration (Sudduth and Hummel 1991; Chaudhary et al. 2012; Kinoshita et al. 2012; Sudduth et al. 2012). Estimation of physical and chemical soil health indicators using VNIR spectra has been less consistent, although some studies have successfully estimated soil texture, aggregate stability, pH, P, and/or K (Chang et al. 2001; Bogrekci and Lee 2005; Vågen et al. 2006; Hu 2013). Physical attributes, such as the cone index (CI), can be measured by in-situ sensors such as a cone penetrometer. The CI is defined as the force per unit base area required to push the penetrometer through a specified increment of soil and reflects soil compaction, soil bulk density, texture, and moisture (ASAE, 2005; Chung et al., 2006). In addition, apparent electrical conductivity (EC_a) reflects numerous soil physical and chemical attributes such as texture, mineralogy, CEC, and moisture (McNeill 1992; Sudduth et al. 2013).

Few studies have evaluated the simultaneous estimation of a broad range of biological, physical, and chemical indicators with the goal of estimating a comprehensive soil health index. Visible near-infrared diffuse reflectance (VNIR) spectra were used by Cohen et al. (2006), Vågen et al. (2006), and Kinoshita et al. (2012) to estimate categorical soil health indices, and by Veum et al. (2015b) to estimate the Soil Management Assessment Framework (SMAF), a continuous soil health index. Veum et al. (2015b) found that VNIR worked well for estimation of the biological components of the SMAF, but did not perform well for estimation of chemical or physical SMAF scores. The SMAF was developed to integrate multiple soil health indicators into a comprehensive index to assess the impact of soil management practices on soil functions, such as ecosystem services, crop production, and/or environmental protection. The SMAF uses non-linear scoring curves and site-specific information (e.g., soil texture, mineralogy, slope, and climate) to translate laboratory measurements into a soil quality score based on a soil's inherent potential (Andrews et al., 2004). The unitless scores are continuous and range from 0 to 100%, where a score of 100% represents a soil that is functioning at its full potential under the given site characteristics. Each scoring curve follows one of three general shapes: "more-is-better" (upper asymptotic sigmoid curve), "less-is-better" (lower asymptote), or "mid-point optimum" (Gaussian function). Currently, the SMAF integrates up to 13 indicators representing soil biological, physical, and chemical functions (Andrews et al., 2004; Stott et al., 2010). The SMAF has been successfully applied to large-scale (Andrews et al., 2004), watershed-scale (Cambardella et al., 2004; Stott et al., 2011), and field-scale (Veum et al., 2014; Veum et al., 2015a) studies of the effects of land use and agricultural management practices on soil quality.

Soils in the Central Claypan Region (Major Land Resource Area 113; USDA-NRCS, 2006) of northeastern Missouri, USA, contain subsurface horizons with 45 to 65% clay (Bray, 1935) that reduce water infiltration (Jung et al., 2007), impede root growth and development (Myers et al., 2007), and contribute to rapid soil degradation (Soil Conservation Service, 1988). Due to the sensitivity of this ecosystem, understanding the effects of management practices on soil health is critical, and development of rapid, low-cost methods using in-field sensors to assess soil health on claypan soils is a priority. The objectives of this study were to evaluate a sensor fusion approach using VNIR spectra in conjunction with EC_a and CI data to estimate (1) multiple biological, physical, and chemical soil health indicators, and (2) SMAF soil health scores.

Materials and Methods

Study Site

The study was conducted on a 10-ha site near Centralia, Missouri (39˚13 N, 92˚07 W). The experimental design was a randomized complete block with three blocks (i.e., replications) where management was the main plot and landscape position was the split plot (Fig. 1). All rotation phases of each cropping system were present each year, and each plot measured 18 m × 189 m (0.35 ha) running east-west parallel to the slope direction. Annual cropping systems included varying nutrient management, crop rotation, cover crops, and tillage. Perennial vegetation systems included permanent cool- and warm-season grasses and legumes under varying management including Conservation Reserve Program (CRP) systems, prairie restoration, and working grasslands (i.e., pasture, forage, and hay production). Soils at the site include Adco silt loam (fine, smectitic, mesic Vertic Albaqualfs) in summit positions with 0 to 1% slopes and Mexico silt loam (fine, smectitic, mesic Vertic Epiaqualfs) in backslope (1-3%) and footslope (1-2%) positions. Detailed descriptions of the management systems are provided in Chaudhary et al. (2012).

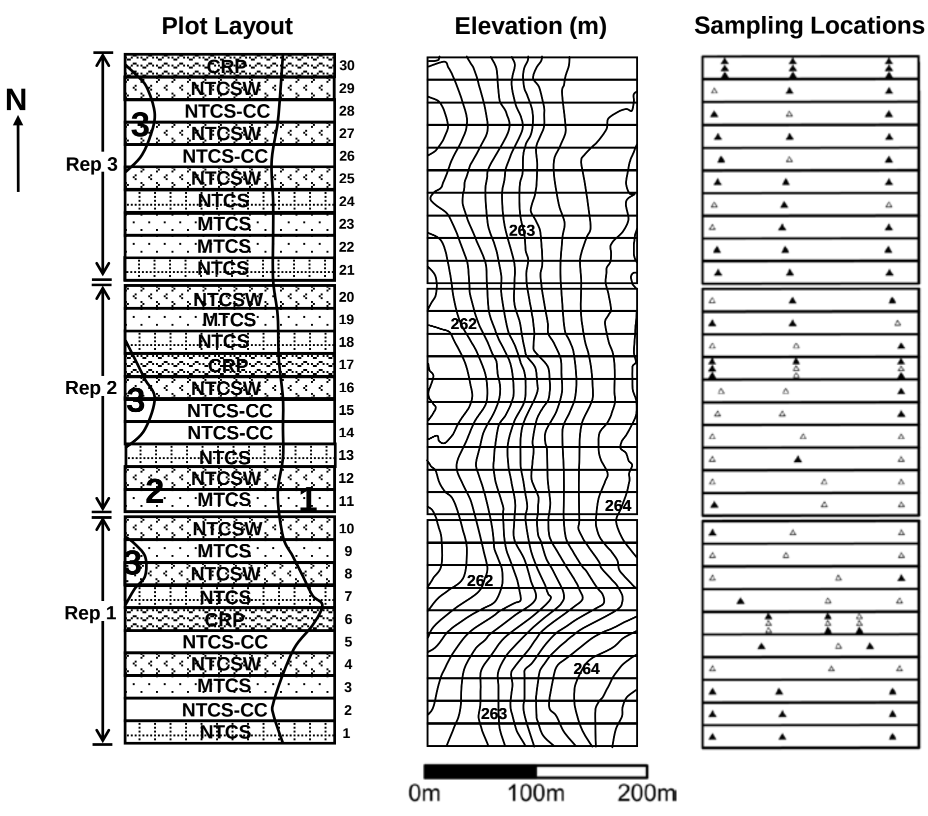

Fig. 1. Plot layout with soil series, cropping systems, elevation, and sampling points. Soils: 1-Adco silt loam, 0-1% slope; 2-Mexico silty clay loam, 1-3%, eroded; 3-Mexico silt loam, 1-2%. Cropping systems: MTCS = mulch-till corn-soybean rotation; NTCS = no-till corn-soybean; NTCSW = no-till corn-soybean-wheat rotation; NTCS-CC = no-till corn-soybean with cover crops; CRP = conservation reserve program. CRP plots were further split lengthwise into three perennial grass systems.

Soil Sampling, CI, and EC_a Data Collection

Soil samples were obtained in the fall of 2010 from each landscape position within each plot (Fig. 1). At each landscape position, three sub-sample points were established in a triangular arrangement within a 3-m radius and three 3.2-cm diameter cores were obtained at each of the sub-sample points. The cores were divided into two depth increments, 0-5 cm and 5-15 cm, and the nine total samples were bulked for each landscape position. Samples were sealed in plastic bags and stored at 4º C prior to processing and laboratory analysis. Near each soil sampling point, a Veris Profiler 3000 (Veris Technologies Inc., Salina, Kansas, USA) collected duplicate in-situ CI (kPa) and EC_a (mS m^{-1}) data. The EC_a and CI data were extracted and averaged over the 6 total probes at each location for the 0-5 cm and 5-15 cm depth increments.

VNIR Spectral Data Collection and Processing

Soil spectral reflectance data were obtained in the laboratory on oven-dried samples from the surface (0-5 cm) and subsurface (5-15 cm) layers using an ASD FieldSpec Pro FR spectrometer (Analytical Spectral Devices, Boulder, CO). Oven-dried samples were crushed and sieved (< 2 mm), then poured into a glass-bottomed cup for spectral collection by a halogen lamp. Samples were scanned from 350 to 2500 nm in 1 nm intervals. Each spectrum, the average of 30 scans, was adjusted using dark current scans. A Spectralon white reference standard (Labsphere Inc., North Sutton, NH) was scanned after every 10 samples to convert the raw spectral data to decimal reflectance. Spectra were obtained in triplicate by rotating the sample cup ca. 60 degrees between sets of scans, and averaged for each sample. Subsequently, VNIR spectra were restricted to 400 – 2500 nm to eliminate regions with a low signal to noise ratio, and averaged across 5 nm intervals. Based on earlier work evaluating the effects of spectral preprocessing (Chaudhary et al., 2012), spectra were log-transformed to absorbance units [log(1/reflectance)] and mean-normalized and centered.

Laboratory Soil Analyses

In brief, soil bulk density and gravimetric moisture content were determined by the Grossman and Reinsch (2002) method. Soil texture was determined using the hydrometer procedure of Gee and Or (2002). Percent silt was calculated by subtracting percent sand and clay from 100. Total soil organic carbon was measured by dry combustion at 950°C (Nelson and Sommers, 1996) on a LECO TruSpec CN analyzer (LECO Corp., St. Joseph, MI) following a negative effervescence test. ß-glucosidase activity was determined by incubating 1 g soil samples with p-nitrophenyl-ß-D-glucoside substrate for 1 h at 37°C (Eivazi and Tabatabai, 1988). Electrical conductivity (Whitney, 1998) and water pH (pHw) were determined on 2-mm, air-dried soil using a 1:1 soil/water ratio (Watson and Brown, 1998). Mehlich III extractable P and K were determined using an inductively coupled plasma–atomic emission spectrograph (Mehlich, 1984).

Soil Management Assessment Framework Scores

Seven soil health indicators representing biological (soil organic C and β-glucosidase activity), physical (bulk density), and chemical (pHw, electrical conductivity, and extractable P and K) soil function categories were included in the SMAF. Each indicator was scored using SMAF algorithms based on sample location-specific details such as soil texture, mineralogy, crop, and climate information. In this study, all samples represented the same organic matter, climate, mineralogy, and weathering factor classes used to parameterize algorithms in the SMAF. Slope categories included slope class one (0-2% slope) in summit and toeslope landscape positions, and slope class two (2-5%) in backslope positions. All of the soil samples in this study were from texture class three (silt and silt loam) or texture class four (silty clay and silty clay loam). Crop-specific factors for pHw, electrical conductivity, and P were based on the dominant species or the most recent crop in rotation systems. The individual indicator scores were combined to generate scores for the biological, physical, and chemical soil function categories and an overall SMAF soil health score for each soil sample using the algorithms published in Andrews et al. (2004), Weinhold et al. (2009), and Stott et al. (2010).

Partial Least Squares Analysis

Data analysis was carried out in Unscrambler version 10.4 (CAMO Inc., Oslo, Norway). Partial least squares (PLS) regression was used to develop models of soil properties and SMAF scores using a 20-fold cross validation procedure to select the number of PLS factors. Models were evaluated and compared using coefficient of determination (R^2), root mean square error of cross-validation (RMSECV), and relative prediction deviation (RPD). The RPD scales model error by population dispersion and facilitates comparison of results from datasets with different degrees of variability (RPD = standard deviation/RMSE). In general, RPD decreases as model performance decreases (Chang et al., 2001; Pirie et al., 2005). Following the categories proposed by Chang et al. (2001), models with $R^2 \geq 0.75$ and RPD ≥ 2.0 were considered the most reliable, models with $R^2 \geq 0.63$ and RPD ≥ 1.6 were considered acceptable, models with $R^2 \geq 0.50$ and RPD ≥ 1.4 demonstrated potential, and all other models were considered poor and unreliable.

Results and Discussion

Summary statistics of the measured soil health indicators and SMAF scores for the dataset can be found in Table 1. Of the seven soil health indicators measured, the coefficient of variation (CV) was the lowest for pHw (5.4%), followed by bulk density (14.8%), and soil organic carbon (37.7%). All other indicators had a CV greater than 50%. Although a high CV does not necessarily imply success, soil properties with a low CV generally are not well-estimated by VNIR. In general, soil properties with a wide range of values may produce more stable and reliable models (Vågen et al., 2006; Bogrekci and Lee, 2007).

Table 1. Descriptive statistics for laboratory-measured soil health indicators and Soil Management Assessment Framework (SMAF) scores. SD = standard deviation, CV = coefficient of variation (%)

Soil Health Indicator	Mean	SD	Min	Max	CV
SOC, g kg^{-1}	16.8	6.4	9.0	41.9	37.7
β-glucosidase activity, mg kg^{-1} h^{-1}	96.7	51.5	17.2	247.2	53.3
K, mg kg^{-1}	83.4	48.4	15.1	353.2	58.0
P, mg kg^{-1}	11.1	8.4	0.0	41.7	75.9
Bulk density, g cm^{-3}	1.26	0.19	0.56	1.57	14.8
pH_w	6.07	0.32	4.95	6.64	5.4
Electrical conductivity, dS m^{-1}	0.14	0.07	0.01	0.59	51.2
SMAF Scores, %	Mean	SD	Min	Max	CV
Overall	71.6	15.4	43.4	98.6	21.4
Biological	48.0	26.9	12.6	99.7	56.0
Physical	79.0	22.8	33.8	99.4	28.9
Chemical	81.6	11.9	54.1	99.6	14.6

Summary statistics for PLS models estimating the laboratory measured soil health indicators developed using VNIR alone and using VNIR in conjunction with CI and/or EC_a data can be found in Table 2. As seen in many other studies, models of soil organic carbon performed well using VNIR alone (R^2 = 0.82, RPD = 2.38), and addition of EC_a and CI did not substantially improve model performance. Given that organic matter and minerals are the primary soil constituents that produce VNIR spectral features, it is not surprising that soil organic carbon models performed well with VNIR alone and did not improve with the addition of other sensor data. Similarly, acceptable models were developed for β-glucosidase activity, which was highly correlated with soil organic carbon (r = 0.81) in this dataset, and likely performed well by proxy. Bulk density and pHw models were only slightly improved by the addition of CI and EC_a data. Using data from all three sensors, RMSE was reduced by 6% for bulk density and 3% for pHw. Models for electrical conductivity, P, and K were poor and unreliable for all sensor combinations. These results emphasize the importance of primary or secondary associations (i.e., surrogate or proxy relationships) between the soil health indicator and VNIR spectral features or auxiliary sensor information for reliable estimation.

Table 2. Partial least squares (PLS) regression cross-validation statistics for models of measured soil properties with visible, near infrared (VNIR) spectra, apparent electrical conductivity (EC_a), and/or cone index (CI) data. NF = number of PLS factors used in the model; RMSECV = root mean square error of cross validation; RPD = standard deviation /RMSE.

Soil Property	NF	R^2	RMSECV	RPD
Soil organic carbon				
VNIR	8	0.82	2.67	2.38
VNIR + EC_a	9	0.82	2.66	2.39
VNIR + CI	9	0.83	2.59	2.45
VNIR + EC_a + CI	9	0.82	2.66	2.39
β-glucosidase activity				
VNIR	6	0.65	30.5	1.69
VNIR + EC_a	7	0.65	30.4	1.70
VNIR + CI	7	0.66	30.0	1.72
VNIR + EC_a + CI	9	0.67	29.6	1.74
Bulk density				
VNIR	8	0.44	0.14	1.33
VNIR + EC_a	9	0.47	0.14	1.37
VNIR + CI	6	0.50	0.13	1.42
VNIR + EC_a + CI	5	0.50	0.13	1.42
Electrical Conductivity				
VNIR	6	0.43	0.056	1.31
VNIR + EC_a	7	0.40	0.057	1.30
VNIR + CI	8	0.44	0.056	1.33
VNIR + EC_a + CI	9	0.42	0.057	1.31
pHw				
VNIR	7	0.59	0.21	1.56
VNIR + EC_a	9	0.61	0.20	1.60
VNIR + CI	9	0.61	0.20	1.60
VNIR + EC_a + CI	9	0.61	0.20	1.60
Phosphorus				
VNIR	6	0.31	7.01	1.20
VNIR + EC_a	6	0.34	6.85	1.23
VNIR + CI	3	0.34	6.89	1.22
VNIR + EC_a + CI	3	0.36	6.77	1.25
Potassium				
VNIR	6	0.35	39.1	1.24
VNIR + EC_a	7	0.35	39.0	1.24
VNIR + CI	6	0.34	39.3	1.23
VNIR + EC_a + CI	5	0.32	39.8	1.22

Summary statistics for PLS models estimating SMAF scores developed using VNIR alone and using VNIR together with CI and/or EC_a data can be found in Table 3. The most improvement was observed for the overall SMAF score between models with VNIR alone (R^2 = 0.69, RPD = 1.82) and models with EC_a and CI (R^2 = 0.78 and RPD = 2.13), demonstrating a 14.3% reduction in RMSE. This suggests that adding EC_a and CI data provided information that related to one or more of the SMAF scoring categories. For individual SMAF categories, modest improvements were seen in the biological and chemical score categories as a result of combining sensor information. Robust estimates of the biological SMAF score were achieved with VNIR alone (R^2 = 0.81, RPD = 2.29), and only improved slightly with the addition of EC_a and CI (R^2 = 0.83, RPD = 2.42). Models for the chemical SMAF score were poor for all combinations of sensors ($R^2 \leq 0.41$, RPD ≤ 1.31), although very slight improvements were observed with EC_a and CI data. In contrast, the physical SMAF score demonstrated a 10% reduction in RMSE with the addition of EC_a and CI to the VNIR spectra, although model performance was still below the acceptable range (R^2 = 0.53, RPD = 1.46). Therefore, the improvement in estimation of the overall SMAF score is most likely due to information related to soil physical characteristics (i.e., soil strength, texture, and mineralogy) that are reflected in the EC_a and CI data.

Table 3. Partial least squares (PLS) regression cross-validation statistics for models of SMAF Scores with visible, near infrared (VNIR) spectra, apparent electrical conductivity (EC_a), and/or cone index (CI) data. NF = number of factors in the model; RMSECV = root mean square error of cross-validation; RPD = standard deviation /RMSE; SMAF = Soil Management Assessment Framework

SMAF Score	NF	R^2	RMSECV	RPD
Overall Score				
VNIR	6	0.69	8.41	1.82
VNIR + EC_a	7	0.74	7.85	1.96
VNIR + CI	6	0.75	7.69	2.00
VNIR + EC_a + CI	8	0.78	7.21	2.13
Biological Score				
VNIR	8	0.81	11.73	2.29
VNIR + EC_a	9	0.82	11.26	2.39
VNIR + CI	8	0.83	11.21	2.40
VNIR + EC_a + CI	9	0.83	11.10	2.42
Physical Score				
VNIR	6	0.42	17.41	1.31
VNIR + EC_a	7	0.47	16.55	1.38
VNIR + CI	4	0.50	16.02	1.42
VNIR + EC_a + CI	5	0.53	15.67	1.46
Chemical Score				
VNIR	5	0.38	9.41	1.27
VNIR + EC_a	6	0.41	9.14	1.30
VNIR + CI	4	0.41	9.12	1.31
VNIR + EC_a + CI	3	0.40	9.14	1.30

Conclusion

On-the-go sensor fusion technology has the potential to provide rapid, cost-effective, and high-resolution soil health assessments to inform site-specific management decisions. Many important soil health indicators do not have strong absorbance or reflectance features in the VNIR range, or do not consistently correlate with primary soil properties that produce VNIR features. Therefore, a sensor fusion approach is ideal for in-field assessment of soil health. The results of this study support using EC_a, and CI sensors with VNIR to improve assessment of biological and physical aspects of soil health. Chemical and fertility-related soil properties that were not well estimated by this sensor fusion combination may require different sensors or supplementary field test kits. Overall, in-field, sensor-based technology has the potential to estimate a comprehensive soil health index for improved sustainability, profitability, and environmental protection.

Acknowledgements and Disclaimer

We acknowledge the following for assistance in data collection, processing and analysis: Robert Kremer, Scott Drummond, Bob Mahurin, Kurt Holiman, Matt Volkmann, Jim Ortbals, Eric Allphin, Alec Sheridan, and Anna Hodge. Mention of trade names or commercial products in this paper is solely for the purpose of providing specific information and does not imply recommendation or endorsement by the United States Department of Agriculture.

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