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Soil moisture and organic matter prediction of surface and subsurface soils using an NIR soil sensor

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Abstract

Sensors are needed to document the spatial variability of soil parameters for successful implementation of Site-Specific Management (SSM). This paper reports research conducted to document the ability of a previously developed near infrared (NIR) reflectance sensor to predict soil organic matter and soil moisture contents of surface and subsurface soils. Three soil cores (5.56 cm dia. × 1.5 m long) were collected at each of 16 sites across a 144 000 km^2 area of the US Cornbelt. Cores were subsampled at eight depth increments, and wetted to six soil moisture levels ranging from air-dry to saturated. Spectral reflectance data (1603–2598 nm) were obtained in the laboratory on undisturbed soil samples. Data were collected on a 6.6 nm spacing with each reflectance value having a 45 nm bandpass. The data were normalized, transformed to optical density [OD, defined as $\log_{10}$ (1/normalized reflectance)], and analyzed using stepwise multiple linear regression. Standard errors of prediction for organic matter and soil moisture were 0.62 and 5.31%, respectively. NIR soil moisture prediction can be more easily commercialized than can soil organic matter prediction, since a reduced number of wavelength bands are required (four versus nine, respectively). © 2001 Elsevier Science B.V. All rights reserved.

Keywords: Soil organic matter; Soil moisture; Spectrophotometry; Optics

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1. Introduction

Quantification of spatial variability of soil parameters is important to the successful implementation of Site-Specific Management (SSM). Soil parameters are known to vary spatially, and with the availability of Global Positioning System (GPS) technology, changes in a soil parameter can be precisely mapped. Research has shown a need for geo-referenced data on more soil parameters, to be able to identify which soil parameter, e.g. nutrient deficiency, soil compaction level, etc. is limiting crop productivity at each grid point or cell throughout the field.

The sampling intensity required to produce reliable predictions of soil parameters (and in turn, accurate maps to use when site-specifically applying soil amendments and/or treatments), is related to the spatial scale of variability of the parameter in question (Frogbrook, 1999). Changes in soil parameters may occur on a finer spatial resolution than can be documented with manual and/or laboratory methods due to cost of the sampling and analysis procedures. Therefore, there is a need for the development of sensors to more accurately characterize within-field variability.

The general observation that soils with higher organic matter contents appear darker formed the basis of the concept that electro-optical sensing of soil organic matter (SOM) might be feasible (Alexander, 1969). Researchers have investigated a number of approaches to automating this general concept, with varying degrees of success. Problems have occurred because soil color and/or reflectance are functions of multiple properties such as moisture, texture, mineralogy, and parent material, as well as SOM.

Laboratory studies of optical estimation of SOM in surface soils has been reported with color data (Steinhardt and Franzmeier, 1979; Page, 1974), and with wide-band and narrow-band spectral reflectance data (Vinogradov, 1981; Sudduth and Hummel, 1993b; Morra et al., 1991; Henderson et al., 1992). Sudduth and Hummel (1993a,b) reported on the development and testing of a near infrared (NIR) reflectance-based sensor using A-horizon Illinois soils. Sudduth and Hummel (1996) extended that work to illustrate the sensor's ability to estimate soil organic carbon, soil moisture, and cation exchange capacity (CEC) of a suite of A-horizon soils obtained over a wider geographic area. That work is extended here through the use of an updated prototype of the original sensor having faster data collection capability (Sudduth and Hummel, 1993c, 1996). This study focused on the prediction of soil organic matter and soil moisture in surface and subsurface layers of an independent set of Illinois soils.

2. Materials and methods

2.1. Soil sample collection and preparation

Soil cores were obtained from 16 sites throughout Illinois in the central US Cornbelt (Table 1). The cores were all taken from natural grass surfaces where the grass was maintained at a height of 10 cm or less. Exact locations of the sample

Table 1
Sample site, soil series, family, and soil organic matter contents

Sample site[a]	Soil series	Family	Depth increment[b]							
			1	2	3	4	5	6	7	8
			Soil organic matter (%)							
Brownstown	Cisne	Fine, montmorillonitic, mesic Mollic Albaqualfs	5.34	2.35	0.69	1.43	0.89	0.43	0.35[c]	0.24[c]
Bondville	Flanagan/Elburn	Fine, montmorillonitic, mesic Aquic Argiudolls/Fine-silty, mixed, mesic Aquic Argiudolls	9.20	4.13	2.17	1.42	0.74	0.63[d]		
DeKalb	Flanagan/Drummer	Fine, montmorillonitic, mesic Aquic Argiudolls/Fine-silty, mixed, mesic Typic Haplaquolls	6.29	5.92	3.20	1.09	2.21	3.01	5.78	
Dixon Springs	Grantsburg	Fine-silty, mixed, mesic Typic Fragiudalfs	3.63	1.35	0.53[d]	0.50	0.46			
Freeport	Dubuque	Fine-silty, mixed, mesic Typic Hapludalfs	7.34[d]	4.04	2.11	1.42	0.82	0.57	0.67	0.48
Belleville	Weir	Fine, montmorillonitic, mesic Typic Ochraqualfs	2.31	1.37	1.05	1.02	0.97	0.66[d]	0.53[c]	
Peoria	Clinton	Fine, montmorillonitic, mesic Typic Hapludalfs	3.40	1.36	0.95	0.59	0.51	0.64		
Ina	Cisne	Fine, montmorillonitic, mesic Mollic Albaqualfs	1.75[d]	1.11	0.99	1.00	0.70	1.23	0.31	
Springfield	Ipava	Fine, montmorillonitic, mesic Aquic Argiudolls	4.69	3.50	2.67	1.86	1.06	0.64	0.69	0.64
Oak Run	Rozetta	Fine-silty, mixed, mesic Typic Hapludalfs	1.47	1.13	0.53	0.43	0.46	0.38	0.35[d]	0.33
Perry	Clarksdale	Fine, montmorillonitic, mesic Udollic Ochraqualfs	3.33	1.66	1.14	0.71	0.61	0.48	0.44	0.33
Olney	Bluford	Fine, montmorillonitic, mesic Aeric Ochraqualfs	1.58	0.96	0.51	0.31	0.31	0.33[c]		
Carbondale	Parke	Fine-silty, mixed, mesic Ultic Hapludalfs	2.33	1.15	0.84[d]	0.60	0.46			
Stelle	Monee	Fine, illitic, mesic Mollic Ochraqualfs	5.48[c]	4.86	5.50	2.12	0.97	0.71	0.57	
Monmouth	Muscatine	Fine-silty, mixed, mesic Aquic Hapludolls	5.00	4.29	1.95	1.05	0.71	0.61	1.94	1.39
Martinsville	Cisne	Fine, montmorillonitic, mesic Mollic Albaqualfs	1.75[d]	0.89	0.60	0.55	0.38	0.32	0.27[c]	

[a] All samples were of either the silt loam or silty clay loam textural classes, which predominate the surface soils in the state of Illinois. See Hollinger and Isard (1994) for a complete geographic location of the sample collection sites.

[b] Depth increment 1 was 10 cm, all other depth increments were 20 cm.

[c] Data are for samples from a single soil core segment.

[d] Data are for samples composited from two soil core segments.

sites and the soil series, family, texture, and total porosity were reported in Hollinger and Isard (1994). The procedure used to obtain undisturbed soil cores was described by Hollinger and Isard (1989).

At each site, three soil cores, up to 1.5 m in length, were collected at 120° intervals around and within 3 m of a neutron access tube. The cores were sectioned at the site into 10 or 20 cm lengths, capped and bagged to prevent loss of water from, or redistribution of water within the core. In the laboratory, each 10 or 20 cm core segment was further divided into 2.5-cm samples. These samples were used to determine soil bulk density, volumetric water content, and for this study, soil organic matter. The top segment of each core was 10 cm, which can most accurately be described as the A_1 horizon (Buckman and Brady, 1960). The remainder of each soil core (which included portions from the A horizon as well as the B horizon) was divided into segments of 20 cm in length, except the bottom segment which varied in length depending upon the total length of the full core. For ease of description in this study, the top 10-cm core segment is called the A horizon, and the remaining core segments are grouped together and called the B horizon. The samples from the top core segment were collected below the grass and residue at the top of the core. However, these samples contained more roots than those taken from the deeper segments.

2.2. Laboratory procedures

2.2.1. Soil sample moisture tension

Six soil moisture levels (saturated, 0.033, 0.1, 0.33, 1.5 MPa, and air-dry) were selected for this study. This broad range of moisture levels was used because moisture levels at depths can vary considerably from those of surface layers in field situations during data collection. Saturated conditions may occur in subsurface layers when drier conditions at the surface would permit field operations to proceed.

The samples taken from the undisturbed soil cores were wetted to a predetermined soil moisture tension level. Samples from the three undisturbed soil cores taken at each collection site were treated as replicates, with a typical replication consisting of 112 randomized soil-depth samples. Soil samples, each still encompassed by a ring of the clear plastic tube insert (Hollinger and Isard, 1989), were placed on a porous ceramic pressure plate. Distilled water, added to the ceramic plate, was allowed to saturate each sample by capillary action. Any shards of plastic tube insert remaining from the cutting process were carefully lifted from the sample surfaces. The ceramic plates and wetted samples were placed in pressure vessels, where the appropriate pressure was applied to obtain the desired moisture tension level in the soil samples. When the sample moisture had equilibrated, the pressure was removed, and the vessel was opened. Each sample was lifted from the ceramic plate using a large spatula, placed under the NIR sensor, and multiple reflectance scans were obtained and stored in the data acquisition computer. The sample was weighed, and then replaced on the ceramic plate. The samples were returned to the pressure vessel, and allowed to equilibrate at the next higher soil moisture tension level. This procedure was repeated until all four moisture tension levels had been established in the samples, and the corresponding reflectance scans obtained. The samples were rewetted to saturation, and reflectance scans and sample weights were collected. Then the samples were allowed to equilibrate under ambient laboratory conditions, and reflectance scans and weights were collected on the air-dried samples. Finally, the samples were removed from the plastic tube insert rings, oven dried at 105 °C for 24 h, and weighed. Gravimetric moisture contents for each sample at each moisture level were calculated from these sample weights.

2.2.2. Soil organic matter

The three replicate samples of each soil at each depth were composited, sieved, and sub-sampled for organic matter analysis. Because direct determination of soil organic matter cannot be done in a completely accurate manner, Nelson and Sommers (1982) recommend that total organic carbon be determined as a measure of organic matter content. In this research, total organic carbon content was determined by dry combustion of duplicate samples of each soil in a LECO Model HF10 induction furnace (Table 1). Organic carbon values were multiplied by 1.72 (Nelson and Sommers, 1982), resulting in the values of soil organic matter data.

2.3. Soil spectral reflectance

The updated prototype sensor (Sudduth and Hummel, 1993c), had a bandwidth of 45 nm, minimal wavelength instability, and was capable of obtaining reflectance data on-line from the dedicated microprocessor within 10 s. Although optical performance and reliability were improved as compared to the initial prototype, the ability of the sensor to estimate soil organic matter and soil moisture was essentially unchanged. Reflectance data were obtained in the laboratory on the undisturbed samples, using the same procedures reported in previous studies (Sudduth and Hummel, 1993b). Within each soil moisture level, data were collected using a randomized complete block design.

3. Results and discussion

3.1. Preliminary data analysis

Means, standard deviations, and coefficients of variation of the laboratory soil moisture data were calculated to assess the quality of the data, and to identify outliers resulting from data recording errors. Twenty seven samples, representing 1.4% of the data, were deemed to be in error and were removed from the dataset. Since the textural class of all the soil cores was either silt loam or silty clay loam, composited moisture data for each soil depth increment (Table 2) can illustrate the moisture content levels in the dataset. Some variability among soil cores collected at each sample site was expected, and the soil moisture contents at the soil tension levels used in this study varied more than was reported in a previous study (Sudduth and Hummel, 1993b). The means of the soil moisture contents were relatively uniform within each moisture tension level, particularly for the B horizon (depth increments 2–8). Soil moisture variability among soils, as reflected by the standard deviation, was also relatively uniform within each moisture tension level for the B horizon.

The spectral reflectance data were transformed from reflectance to optical density [OD, defined as $\log_{10}$ (1/reflectance)]. The initial spectral data ranged from 1603 nm to 2598 nm, but because of low signal-to-noise ratios at the ends of the spectra, only data in the 1623 nm to 2467 nm range (6.6 nm spacing—129 data points) were included in the analyses. The spectral reflectance data were normalized by dividing each reflectance value by the mean reflectance of the 129 bands within each spectra, creating a second data set with a mean of 1.0. These data were also transformed to OD. Correlations of soil spectral OD data (both unnormalized and normalized) and chemical/physical property data were accomplished using step-wise multiple linear regression (SMLR) for each depth increment and for the overall dataset. The maximum r^2 improvement (MAXR) model selection method in SAS Stepwise Regression (STEPWISE) procedure (SAS Institute, 1999) was chosen, as it was noted as being superior to other step-wise techniques and 'almost as good' as evaluating all possible regressions. The SAS Generalized Linear Model (GLM) procedure was applied to both the unnormalized and normalized datasets, and for both soil organic matter and soil moisture, to consider the effect of the class variables-soil, moisture, depth and replication. All class variables, with the exception of replication, were significant at the $P < 0.05$ level for both the unnormalized and normalized datasets. The best linear regression models consisting of ODs were selected by STEPWISE, which was allowed to include additional wavelengths until

Table 2
Means and standard deviations of gravimetric soil moisture contents at each soil depth increment

Depth increment[a]	Moisture level					
	Saturated	0.033 MPa	0.1 MPa	0.33 MPa	1.5 MPa	Air-dry
	Mean soil moisture content (% d.b.), S.D. (%)					
1	56.6 (19.7)	37.3 (7.9)	31.6 (9.9)	28.1(11.6)	22.3 (11.0)	4.9 (2.3)
2	51.3 (8.9)	36.0 (6.6)	30.5 (6.2)	25.6 (6.6)	19.6 (6.9)	4.0 (1.4)
3	51.4 (8.2)	37.8 (7.6)	32.8 (6.9)	27.8 (5.7)	22.0 (5.5)	4.6 (1.6)
4	50.1 (9.8)	37.3 (6.8)	34.5 (6.7)	30.1 (5.4)	25.6 (5.4)	5.7 (2.0)
5	46.9 (8.2)	36.6 (6.0)	32.7 (5.4)	28.1 (4.3)	23.7 (3.7)	5.3 (2.0)
6	47.3 (8.8)	36.1 (6.0)	30.5 (4.5)	26.0 (3.8)	21.2 (3.7)	4.2 (1.1)
7	44.0 (10.8)	34.2 (7.2)	29.9 (5.7)	25.4 (4.8)	20.4 (4.5)	4.1 (1.2)
8	53.9 (6.2)	40.1 (4.6)	33.2 (3.8)	26.9 (2.9)	20.7 (3.4)	4.7 (1.7)
Overall	50.2(11.5)	36.8 (6.8)	32.0 (6.7)	27.4 (6.6)	22.2 (6.5)	4.7 (1.8)

[a] Depth increment 1 was 10 cm, all other depth increments were 20 cm.

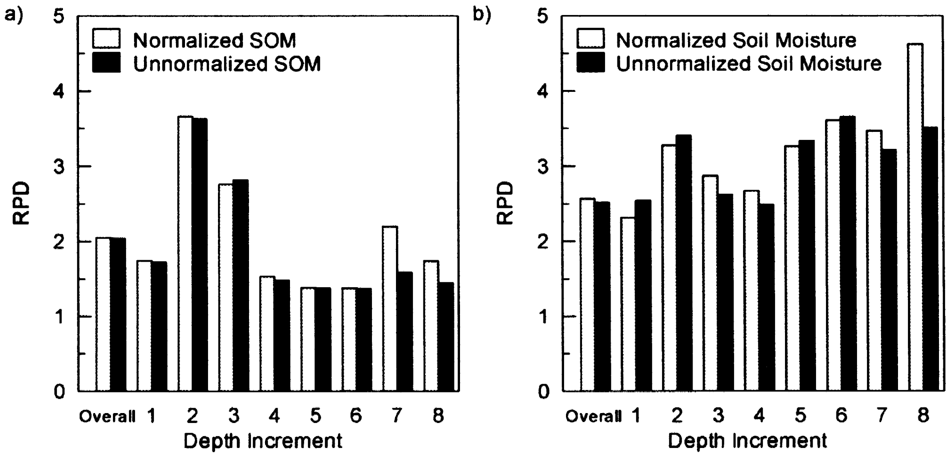

Fig. 1. Comparison of the prediction capability of the unnormalized and normalized datasets for: (a) soil organic matter; and (b) soil moisture, using RPD, the ratio of standard deviation to standard error of prediction (SEP).

any one of the parameter estimates was determined to be insignificant at the $P < 0.05$ level. This procedure was carried out on the overall dataset (both unnormalized and normalized), and on the subsets of the optical density data for each of the soil depth levels (both unnormalized and normalized). Although some level of overfitting was possible with this scenario, it did allow a comparison of the predictive capability with the two datasets.

RPD, the ratio of standard deviation to standard error of prediction (SEP) was used to compare the predictive capability of the unnormalized and normalized datasets (Fig. 1). RPD is a useful measure of fit when comparing results on datasets containing differing degrees of variability, with a higher RPD indicating a more accurate prediction (Williams, 1987). The predictive capability was slightly better, considering all depth increments, with the normalized dataset as compared to the unnormalized dataset (Fig. 1), and subsequent analyses were carried out only on the normalized dataset.

3.2. SOM prediction

Soil carbon ranged from 0.15 to 5.35% (0.27–9.20% SOM), as compared to the 0.45–3.16% carbon range of the calibration data reported in a previous study of A-horizon soils (Sudduth and Hummel, 1993b). The SOM ranges for this study were 1.47–9.20 and 0.27–5.92% for the A-horizon and B-horizon segments, respectively, of the soil cores in this study (Table 1).

A calibration dataset was formed by randomly selecting two of the three replicate observations for each soil/moisture/depth combination. The remaining replicate observation was reserved for prediction purposes. Stepwise multiple linear regression was accomplished using the SAS STEPWISE procedure. In these analyses, as well as all other SMLR analyses, statistical significance of the individual terms was observed to ensure that overfitting of the data did not occur. For the overall normalized dataset, 20 valid wavelength terms (Table 3) were returned by the SMLR program, with a standard error of prediction (SEP) of 0.78% organic matter and an RPD of 2.11 (Table 4). Because of increased standard errors for the A-horizon soils (data not shown), this soil layer did not receive further analysis. For the B-horizon data subset, 18 valid wavelength terms (Table 3) were returned and the standard error of prediction (SEP) was reduced to 0.62% organic matter, but because the range of soil organic matter was reduced, the RPD dropped to 2.05 (Table 4). To approximate narrow bandpass filters, ODs were combined (6 wavelength terms each), resulting in 21 terms, with an optical bandpass of $\sim$78 nm, ranging from 1623 to 2460 nm. Using 13 combined wavelength terms, similar results, in terms of the RPD, were obtained (Table 4). Initially, the SEC and SEP values decreased rapidly as additional terms were introduced, but as the number of included terms increased, the rate of reduction of SEC and SEP decreased (Fig. 2) and both SEC and SEP asymptotically approached minimum values. Using a cutoff of an SEP within 0.02 of the minimum obtained, nine 78-nm bandpass terms in the calibration equation for the B-horizon dataset resulted in an SEP of 0.62% organic matter and a RPD of 2.06 (Table 4). This prediction capability was the same, in terms of the RPD, as that obtained with the larger number of statistically valid terms.

Table 3
Terms identified by stepwise multiple linear regression for predicting soil organic matter using a normalized dataset collected with an NIR soil sensor

Soil depth Increments included	No. terms	Center wavelengths of terms
Total valid terms[a]		
Overall, 45 nm bandpass	20	1636, 1676, 1702, 1709, 1781, 1946, 1959, 1979, 2038, 2117, 2164, 2203, 2269, 2295, 2309, 2348, 2361, 2414, 2434, 2447
B horizon, 45 nm bandpass	18	1630, 1682, 1755, 1874, 1939, 1966, 1986, 2005, 2038, 2065, 2124, 2183, 2203, 2309, 2348, 2361, 2388, 2414
B horizon, 78 nm bandpass	13	1640, 1679, 1798, 1877, 1996, 2035, 2075, 2154, 2193, 2272, 2312, 2351, 2391
SEP within 0.02 of min[b]		
Overall, 45 nm bandpass	9	1630, 1735, 1986, 2038, 2137, 2216, 2309, 2348, 2408
B horizon, 45 nm bandpass	8	1630, 1722, 1874, 2164, 2203, 2295, 2361, 2440
B horizon, 78 nm bandpass	9	1640, 1679, 1758, 2035, 2154, 2193, 2312, 2351, 2431

[a] The maximum number of statistically significant terms by SMLR.
[b] The number of terms necessary to achieve a SEP within 0.02 of the minimum SEP.

Table 4
Summary of stepwise multiple linear regression results for determining soil organic matter prediction ability of an NIR soil sensor using the normalized dataset

Soil depth Increments included	No. terms	r^2	SEC[a]	SEP[b]	RPD[c]
Total valid terms[d]					
Overall, 45 nm bandpass	20	0.79	0.75	0.78	2.11
B horizon, 45 nm bandpass	18	0.77	0.61	0.62	2.05
B horizon, 78 nm bandpass	13	0.76	0.63	0.62	2.06
SEP within 0.02 of min[e]					
Overall, 45 nm bandpass	9	0.77	0.79	0.79	2.06
B horizon, 45 nm bandpass	8	0.72	0.67	0.64	2.00
B horizon, 78 nm bandpass	9	0.73	0.66	0.62	2.06

[a] SEC (standard error of calibration) is the standard error of the estimate in the calibration data in percent soil organic matter.
[b] SEP (standard error of prediction) is the standard error of the estimate in the validation data in percent soil organic matter.
[c] RPD is the ratio of standard deviation to SEP.
[d] The maximum number of statistically significant terms by SMLR.
[e] The number of terms necessary to achieve a SEP within 0.02 of the minimum SEP.

The prediction of soil organic matter (Fig. 3) shows a tendency to under-predict at the higher moisture levels, and the tendency remains when the A-horizon data are removed from the dataset. A relatively narrow range of SOM in the samples, which is typical of B-horizon soils, resulted in reduced coefficients of determination and increased SEPs (Table 4) as compared to earlier reported research on surface soils (Sudduth and Hummel, 1993b, 1996), and removal of the A-horizon data further reduced the organic matter range.

3.3. Soil moisture prediction

Six soil moisture levels, ranging from saturated to air-dry, were included in this study. Mean soil moisture was 50.2, 36.8, 32.0, 27.4, 22.2, and 4.7% for the moisture tension levels ranging from saturated to air-dry, respectively (Table 2). The low standard deviations of the soil moisture levels across soil cores were attributed to the relatively uniform clay content and reduced organic matter content in the B horizon of these soils.

Using SMLR with the overall normalized dataset, 12 valid wavelength terms (Table 5) were returned, with a standard error of prediction (SEP) of 6.38% soil moisture and an RPD of 2.36 (Table 6). For the B-horizon data subset, 13 valid wavelength terms (Table 5) were returned. The SEP decreased to 5.15% soil moisture, and the RPD increased to 2.87. When ODs were combined to produce 21 possible predictive terms, only 8 terms were significant, with essentially no change in either SEP or RPD (Table 6). Using an arbitrary cutoff on further reduction in the RPD, only five 45-nm bandpass terms in the calibration equation resulted in a

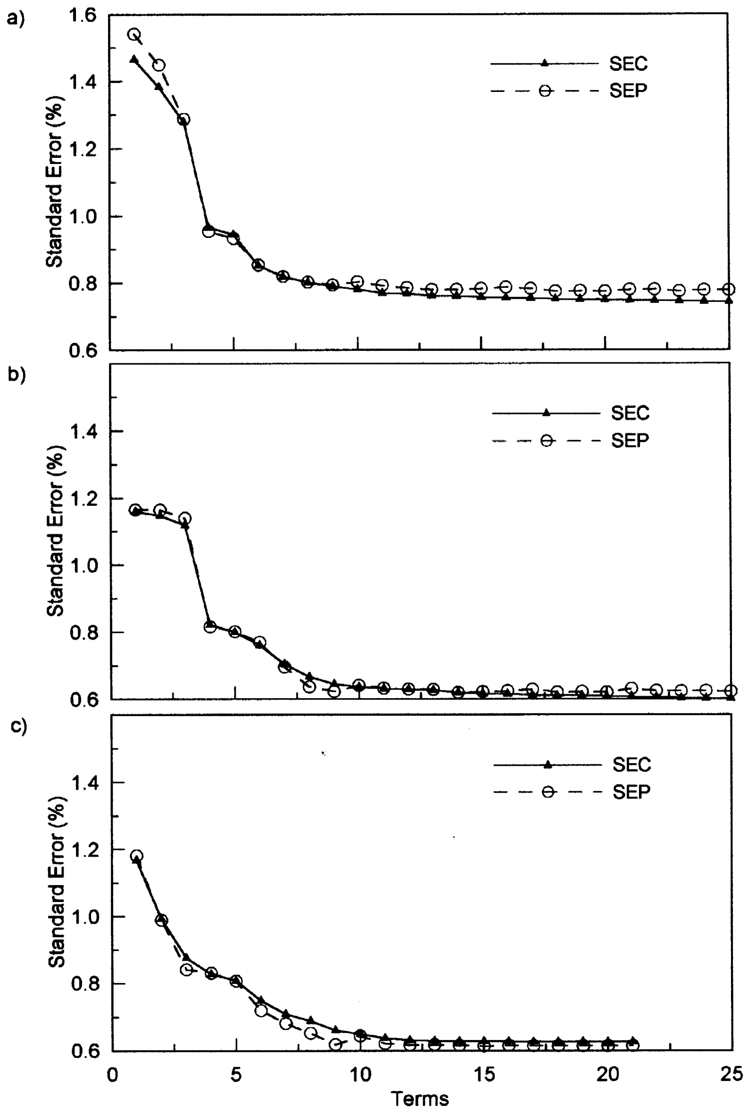

Fig. 2. Comparison of Standard Error of Calibration (SEC) and Standard Error of Prediction (SEP) values obtained with SMLR for predicting soil organic matter. From top to bottom, comparisons are for: (a) the combined A- and B-horizon normalized dataset using 45-nm bandpass terms; (b) the B-horizon normalized dataset using 45-nm bandpass terms; and (c) the B-horizon normalized dataset using 78-nm bandpass terms.

Fig. 3. Comparison of observed and predicted soil organic matter using reflectance data from undisturbed soil core segments. From top to bottom, predictions are for: (a) the combined A- and B-horizon dataset using all valid SMLR terms (45-nm bandwidth); (b) the B-horizon dataset using all valid SMLR terms (45-nm bandwidth); (c) the B-horizon dataset using all valid SMLR terms (78-nm bandwidth); and (d) the B-horizon dataset using only those SMLR terms needed for an SEP within 0.02 of the minimum SEP (78-nm bandwidth). Left column-prediction of the calibration dataset; right column-prediction of the prediction dataset.

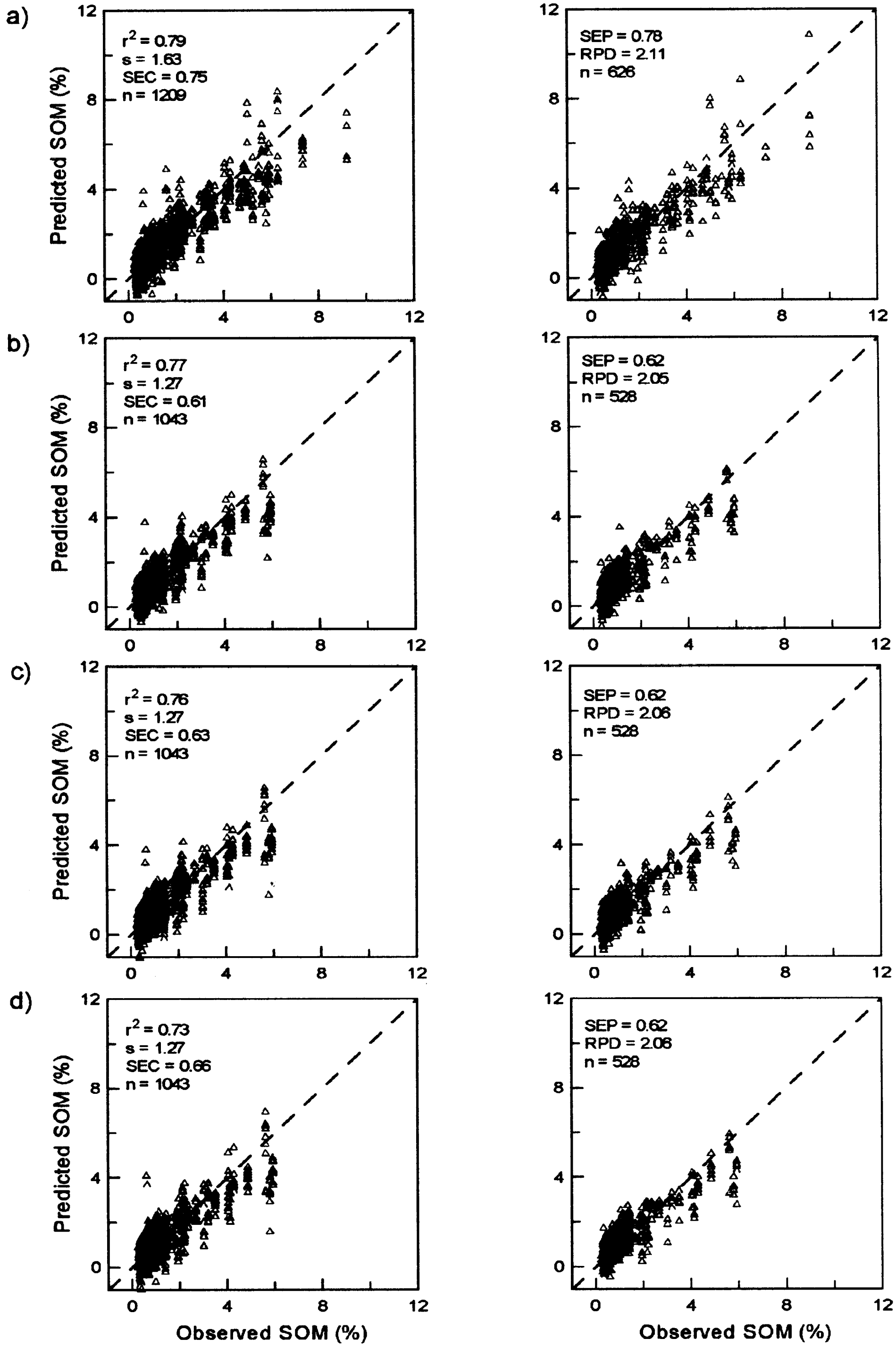

Fig. 3. (*Continued*)

Table 5
Terms identified by stepwise multiple linear regression for predicting soil moisture using a normalized dataset collected with an NIR soil sensor

Soil depth Increments included	No. terms	Center wavelengths of terms
Total valid terms[a]		
Overall, 45 nm bandpass	12	1623, 1748, 1775, 1781, 1788, 1860, 1880, 1926, 1972, 2025, 2131, 2216
B horizon, 45 nm bandpass	13	1623, 1821, 1887, 2032, 2038, 2085, 2117, 2150, 2164, 2230, 2243, 2289, 2309
B horizon, 78 nm bandpass	8	1640, 1837, 1877, 2035, 2114, 2233, 2272, 2312
SEP within 0.02 of min[b]		
Overall, 45 nm bandpass	5	1623, 1762, 2025, 2131, 2223
B horizon, 45 nm bandpass	5	1860, 1874, 2025, 2117, 2230
B horizon, 78 nm bandpass	4	1837, 2035, 2114, 2233

[a] The maximum number of statistically significant terms by SMLR.
[b] The number of terms necessary to achieve a SEP within 0.02 of the minimum SEP.

SEP of 5.24% soil moisture and an RPD of 2.82. When the response of narrow bandpass filters was approximated, only four terms were used in the calibration equation, and the SEP increased to 5.31% soil moisture while RPD was reduced to 2.78 (Table 6). The rapid reduction in standard error for soil moisture data, as additional terms were introduced by SMLR, for the B-horizon dataset is evident in Fig. 4(b, c). The low number of wavelength terms for soil moisture prediction in the B horizon is of special interest in applications such as moisture compensation in soil cone penetrometers.

The prediction of soil moisture (Fig. 5) shows a tendency to under-predict at the higher moisture levels, and, as with SOM, the tendency was unaffected by the removal of the A-horizon data from the dataset. A layer of water may have been present on the surface of some of the saturated samples during the reflectance data collection, which would have introduced specular reflectance and hampered the ability of the NIR sensor to capture soil spectral reflectance. A lower moisture content at the sample surface presented to the sensor than within the remainder of the sample is more likely for the saturated samples, because of moisture movement due to gravity. This situation would contribute to the tendency to under-predict at higher gravimetric (observed) soil moisture contents (Fig. 5). The SEP values for B-horizon soil moisture were three times greater than earlier reported values for

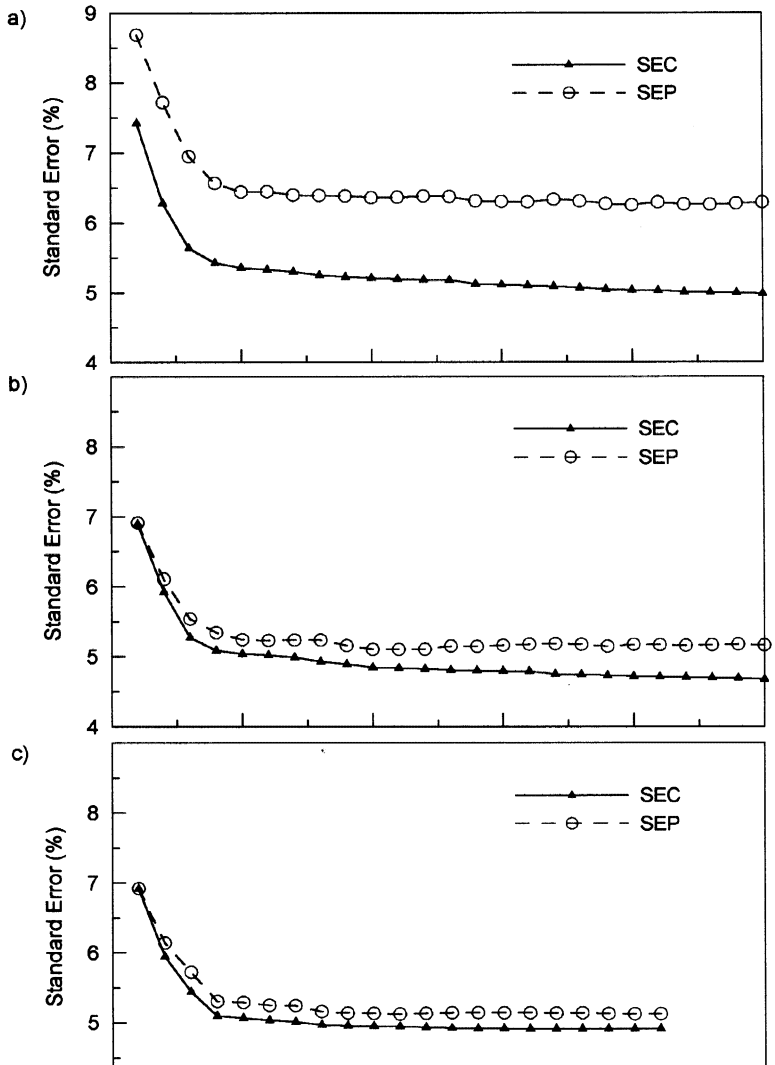

Fig. 4. Comparison of Standard Error of Calibration (SEC) and Standard Error of Prediction (SEP) values obtained with SMLR for predicting soil moisture content. From top to bottom, comparisons are for: (a) the combined A- and B-horizon normalized dataset using 45-nm bandpass terms; (b) the B-horizon normalized dataset using 45-nm bandpass terms; and (c) the B-horizon normalized dataset using 78-nm bandpass terms.

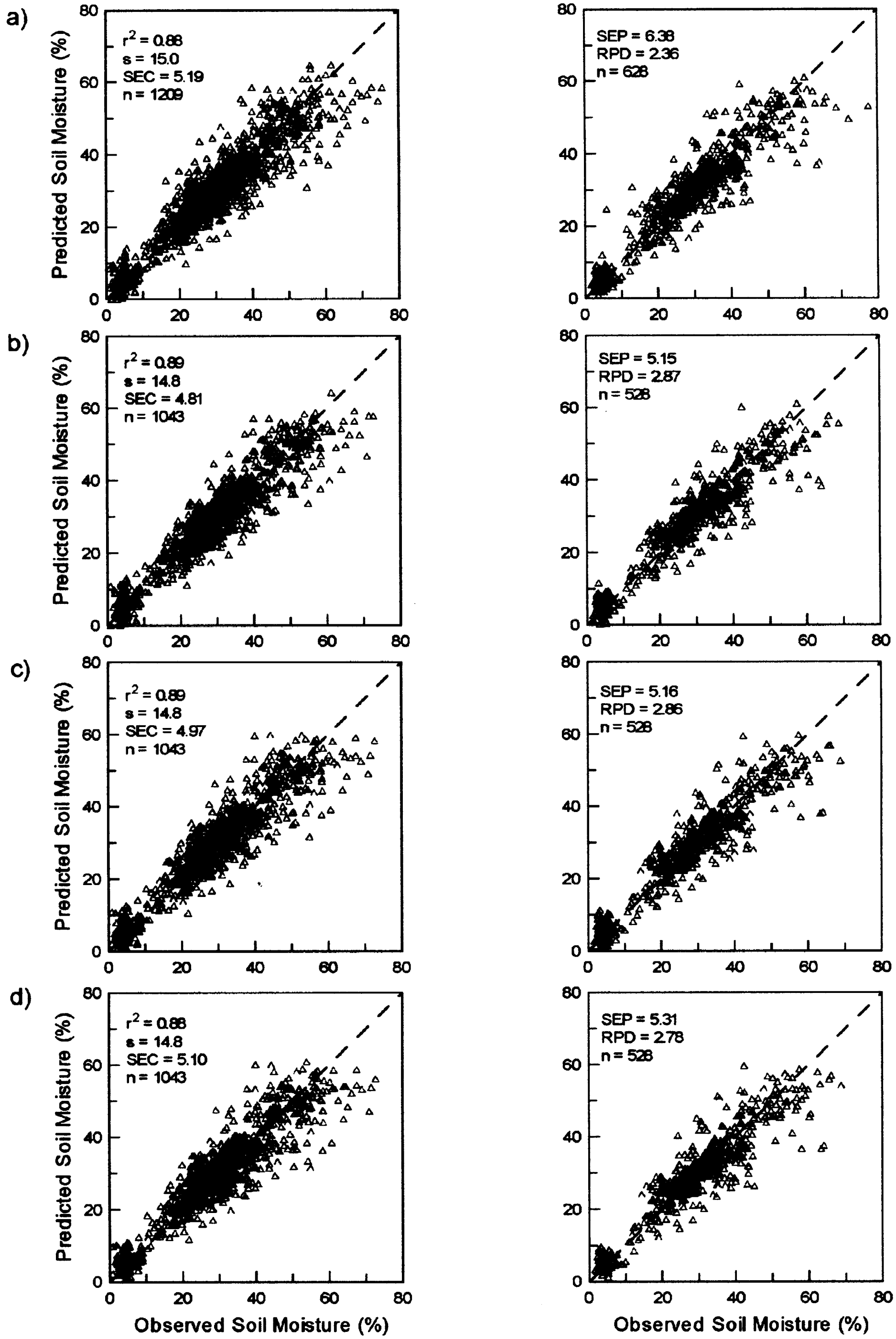

Fig. 5. (*Continued*)

Table 6
Summary of stepwise multiple linear regression results for determining soil moisture prediction ability of an NIR soil sensor using the normalized dataset

Soil depth Increments included	No. terms	r^2	SEC[a]	SEP[b]	RPD[c]
Total valid terms[d]					
Overall, 45 nm bandpass	12	0.88	5.19	6.38	2.36
B horizon, 45 nm bandpass	13	0.89	4.81	5.15	2.87
B horizon, 78 nm bandpass	8	0.89	4.97	5.16	2.86
SEP within 0.2 of min[e]					
Overall, 45 nm bandpass	5	0.87	5.35	6.44	2.34
B horizon, 45 nm bandpass	5	0.88	5.04	5.24	2.82
B horizon, 78 nm bandpass	4	0.88	5.10	5.31	2.78

[a] SEC (standard error of calibration) is the standard error of the estimate in the calibration data in percent soil organic matter.
[b] SEP (standard error of prediction) is the standard error of the estimate in the validation data in percent soil organic matter.
[c] RPD is the ratio of standard deviation to SEP.
[d] The maximum number of statistically significant terms by SMLR.
[e] The number of terms necessary to achieve a SEP within 0.02 of the minimum SEP.

A-horizon soils (Sudduth and Hummel, 1993c), indicating a reduced soil moisture prediction capability. The portion of the reduction in predictive capability that can be attributed to the use of undisturbed soil core segments in this study, as compared to cleaned, ground, and sieved samples in the previously reported study, is unknown.

4. Conclusions

These tests of a prototype NIR reflectance sensor demonstrated that the technology may be applicable for the estimation of soil organic matter and soil moisture in B-horizon soils. Additional work will be necessary to extend the applicability beyond the group of silt loam and silty clay loam soils (Central US Cornbelt) included in this project.

Fig. 5. Comparison of observed and predicted soil moisture using reflectance data from undisturbed soil core segments. From top to bottom, predictions are for: (a) the combined A- and B-horizon dataset using all valid SMLR terms (45-nm bandwidth); (b) the B-horizon dataset using all valid SMLR terms (45-nm bandwidth); (c) the B-horizon dataset using all valid SMLR terms (78-nm bandwidth); and (d) the B-horizon dataset using only those SMLR terms needed for a SEP within 0.2 of the minimum SEP (78-nm bandwidth). Left column-prediction of the calibration dataset; right column-prediction of the prediction dataset.

The ability to predict organic matter and soil moisture using undisturbed cores is a definite step toward in situ measurement of these soil parameters. The predictive capabilities of the NIR sensor for soil organic matter and soil moisture for B-horizon soils were not as accurate as for prepared samples of surface soil layers, but may be sufficient for site-specific management if multiple predictions can be aggregated. Sensing and mapping of soil organic matter in the B-horizon as well as in the surface layer could lead to a better understanding of soil moisture retention, which is a major factor in plant growth and productivity.

The use of only four wavelength bands for the prediction of soil moisture also has implications in the commercialization of the sensor technology. A small number of fixed bandwidth filter elements would be more economical and rugged than the components used in the current prototype. This approach might find application as a component of a sensor for some other soil parameter, in the same manner as a grain moisture sensor is an integral part of a yield monitor.

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