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Soil property sensing for site-specific crop management

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Abstract

Site-specific crop management (SSCM) aims to improve production efficiency by adjusting crop inputs, especially fertilizers and agro-chemicals, to varying local conditions within a field. Sensors are needed to obtain site-specific data on factors affecting crop growth and yields, such as nutrient status, weed pressure, soil moisture status, landscape position, soil organic matter (SOM) content, soil acidity, and depth to a restrictive layer.

Two SOM sensors have been licensed for commercial development: (1) a single-wavelength sensor that must be recalibrated for the soils and moisture conditions that prevail at the time of use, and (2) a multiple-wavelength sensor which can utilize a single calibration to predict SOM over a range of soil moistures and a range of soil types that occur within a geographical range of several hundreds of kilometers. The single-wavelength sensor requires operator acceptance of the need for frequent recalibration, but is relatively inexpensive and rugged. The multiple-wavelength sensor uses a single calibration applicable over a broader range of soil types and soil moistures, and can also be used to sense soil moisture and cation exchange capacity (CEC), but uses complex technology. A simple inexpensive sensor that can classify soils according to soil moisture has also been developed. Sensors for other soil parameters are being sought, and progress has been reported on nutrient and depth-to-claypan sensing.

Keywords: Soil organic matter; Soil nitrate; Soil moisture; Depth-to-claypan; Cation exchange capacity

1. Introduction

Present management practices, such as using mean soil fertility level and yield goals, assume that the soil within a single field is homogeneous. In reality the soil in a

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field is heterogeneous and large variations may be encountered within a single field. Site-specific crop management (SSCM) aims to improve production efficiency by adjusting crop inputs, especially fertilizers and agro-chemicals, to varying conditions within a field. Input application may be based on any factor or combination of factors affecting crop growth and yields, such as nutrient status, weed pressure, soil moisture status, landscape position, soil organic matter (SOM) content, soil acidity, or depth to a restrictive layer. Today, low-cost powerful computers, real-time controllers, accurate navigational systems, and developments in electronic sensors have been combined to provide the technology necessary to make SSCM a reality (Auernhammer and Muhr, 1991).

Measurement of the soil properties that affect plant growth is a basic task in SSCM. The spatial and temporal intensity at which each property must be measured is a function of its variability. Some parameters, such as soil nitrate content and soil moisture content, can change rapidly (both spatially and temporally) and must be measured in real-time or near real-time to be useful for input control. Other parameters, such as organic matter content and depth to a restrictive soil layer (such as a claypan) will vary over a much longer time frame, and can be measured off-line on a multi-year frequency. Likewise, spatial measurement intensity can be related to the spatial variation in the property being measured. Often it may be necessary to sample initially on a fine mesh to define the spatial variability. Depending on the variability, subsequent measurements may then be made on a coarser scale to provide the information needed.

Electronic, automated sensing of soil properties is essential for efficient implementation of SSCM strategies. Although many soil properties can currently be quantified by traditional methods (such as collecting soil samples for analysis of nutrient levels), widespread adoption of SSCM will depend on automation to improve the efficiency of the soil property analysis process. A number of soil properties have been the subject of recent sensor research, including soil moisture for planting depth control (Carter and Chesson, 1993), soil texture (Liu et al., 1993), nitrate concentration (Adsett and Zoerb, 1991), and SOM (Shonk et al., 1991, Sudduth and Hummel, 1993a, b). Examples from our work on the development of SOM sensors utilizing visible and near infrared (NIR) light reflectance are discussed. Research experiences in sensing of other soil properties, including moisture and cation exchange capacity (CEC) using light reflectance, soil nutrients using ion selective field effect transistors (ISFETs), and sensing the depth-to-claypan [1] using electromagnetic induction (EM) methods of measuring soil conductivity, are also presented.

2. SOM sensing

In midwestern U.S. crop production, many producers use soil-applied herbicides. Some herbicides are adsorbed by SOM, requiring higher herbicide rates to obtain the desired level of weed control. In fields having varying SOM levels, the herbicide application rate might be adjusted according to SOM levels to reduce pesticide use.

[1] A high-clay subsurface soil layer common to large areas of midwestern U.S.

The general observation that soils with greater organic matter contents appear darker formed the basis of the concept that electro-optical sensing of 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 reflectance are a function of properties such as moisture, texture, mineralogy, and parent material, as well as SOM.

Optical sensing of SOM has been accomplished with color data, and with wide-band and narrow-band spectral reflectance data. Soil color properties correlated with SOM have included the Munsell coordinates of hue, value, and chroma (Steinhardt and Franzmeier, 1979), as well as a number of Commission Internationale de l'Eclairage (CIE) color space coordinates (Page, 1974). In general, color has been a good estimator of SOM only when limits were imposed on the variability of the other soil parameters which affect soil reflectance. A variety of data types and calibration methods have been used to correlate percent reflectance with SOM (Sudduth et al., 1991). The best results with visible reflectance data have been obtained with red light (Vinogradov, 1981), while the most predictive NIR wavelengths have ranged from 1700 to 2600 nm (Morra et al., 1991; Henderson et al., 1992).

2.1. Sensing for automatic herbicide rate control

Several researchers have developed optical SOM sensors to be used as a control input for variable rate herbicide application. These sensors have ranged from simple, single-wavelength devices to dedicated spectrophotometers capable of acquiring reflectance data at a number of wavelengths (Sudduth et al., 1991). Krishnan et al. (1980) correlated multiple-band reflectance characteristics in the 400–2400 nm range and SOM for ten Illinois soils at four moisture levels. Better correlations were obtained with visible range data than with NIR data. A first derivative model using optical density data yielded an r^2 of 0.85 with the calibration dataset. Pitts et al. (1986) could not obtain satisfactory correlations when using this model with an expanded set of 30 Illinois soils ranging from 0.77 to 5.01% SOM. However, they were able to successfully predict a range of SOM for each of the 30 soils using an exclusion algorithm and polychromatic (white), green, and red reflectance data. The width of the prediction range for each soil was between 1 and 3% SOM, with an average width of 1.4% SOM.

Griffis (1985) developed and tested a SOM sensor consisting of an incandescent source and silicon phototransistor mounted in a light-proof housing. An r^2 of 0.75 was obtained in laboratory tests with a set of 18 air-dry Arkansas soils ranging from 0.19 to 1.98% organic carbon. Kocher and Griffis (1989) reported on an elevating chain and horizontal belt system which was used to convey soil past the sensor developed by Griffis (1985). In laboratory tests with sieved, air-dry soil, the conveying mechanism–sensor combination was successful in locating a step change in soil type.

Gunsaulis et al. (1991) studied the effect of soil surface structure on reflectance from a red (660 nm) light-emitting diode (LED) source. Surface preparation was by sieving the air-dry soil and then scraping or rolling the surface before

Table 1
Laboratory performance of recent electro-optical SOM sensors

Investigator/Sensor	Calibration					Measures of fit		
	Wavelengths		Method [a]	Soils [b]	Moisture levels [c]	r^2	SE [d]	RPD [e]
	Range (nm)	No.						
Gunsaulis et al. (1991)								
diffuse/specular sensor	660	1	LR	20 AR	AD	0.61	0.32 c	1.6 c
diffuse sensor	660	1	LR	20 AR	AD	0.48	0.37 c	1.4 c
both sensors	660	1	MLR	20 AR	AD	0.73	0.27 c	1.9 c
Shonk et al. (1991)	660	1	LR	11–12 IN [f]	AD	0.80–0.91 [g]	– [h]	–
	660	1	LR	11–12 IN [f]	FC	0.87–0.95 [g]	–	–
	660	1	ILR	12 IN [f]	AD	0.98	–	–
	660	1	ILR	12 IN [f]	FC	0.98	–	–
Smith (1991)	543– 835	4	SMLR	30 IL	FC and WP	0.61	0.79 p	1.2 p
	531–1004	24	PLSR	30 IL	FC and WP	0.71	0.64 p	1.8 p
Sudduth and Hummel (1993b)	1640–2640	26	PLSR	30 IL	FC and WP	0.89	0.40 p	2.9 p
Sudduth et al. (1990)	1640–2640	26	PLSR	34 CB	FC and WP	0.86	0.48 p	2.5 p
	1640–2640	26	PLSR	63 US	FC and WP	0.67	0.69 p	1.7 p
Sudduth and Hummel (1993c)	1890–2450	6	SMLR	30 IL	FC and WP	0.77	0.46 p	2.2 p

[a] Calibration data analysis methods: LR = linear regression; MLR = multiple linear regression; ILR = inverse linear regression; SMLR = stepwise multiple linear regression; PLSR = partial least squares regression.
[b] The number of soils in the dataset and the U.S. state where the soil samples were collected. Datasets are from Arkansas (AR), Indiana (IN), Illinois (IL), U.S. Cornbelt (CB), and entire United States (US). CB dataset includes soils from the U.S. Cornbelt states of Illinois, Missouri, Indiana, and Ohio.
[c] Soil moisture levels: AD = air-dry; FC = field capacity (0.033 MPa moisture tension); WP = wilting point (1.5 MPa moisture tension).
[d] SE is the standard error of the estimate, in percent organic matter. Data suffixed by a "c" is a standard error of calibration (SEC), the SE in the calibration dataset. A "p" indicates standard error of prediction (SEP), the SE in a validation dataset.
[e] RPD is the ratio of standard deviation of SE; a larger RPD indicates a more accurate prediction.
[f] Soil samples collected from within a single soil catena.
[g] Range of fit obtained from three individual soil catenas.
[h] Dashes indicate unavailable data.

obtaining reflectance measurements. Two sensor geometries were tested; one which measured only diffuse reflectance and one which measured both diffuse and specular reflectance components. The 20 Arkansas soils used ranged from 0.47 to 2.1% organic matter. The best results ($r^2 = 0.61$) were obtained with absorbance data from the diffuse-specular sensor, the largest sieve size (3.66 mm) and a scraped soil surface (Table 1). Attempts to minimize surface structure effects by passing the soil through small sieves and rolling the surface smooth resulted in weaker ($r^2 = 0.40$) correlations with SOM. Improved results ($r^2 = 0.73$) were obtained with multiple linear regression on data obtained from both sensors (Table 1).

The sensors described above, which generally used only one or a few pieces of spectral information (in terms of color coordinates or reflectance values) did not achieve the goal of providing optical estimation of SOM over a wide (entire state or larger) geographic range. Armed with this knowledge, researchers sought to improve their results either by using a single-wavelength sensor requiring recalibration for each soil catena[2] in which the sensor operated, or by developing instruments which were capable of providing additional spectral information from many narrow wavelength bands.

2.2. Single-wavelength sensing

In the single-wavelength sensing approach, researchers at Purdue University (Fernandez et al., 1988) correlated Munsell color with SOM for a given soil catena, hypothesizing that there would be a closer relationship than those previously reported for wider geographic areas. Samples collected from three soil series in each of two catenas yielded strong correlations between SOM and Munsell value (moist soil $r^2 = 0.92$, dry soil $r^2 = 0.94$). Different calibrations were required at the two moisture levels, and the calibrations developed were applicable only within the catenas studied, containing only silt loam and silty clay loam soils.

Shonk et al. (1991) built upon the work of Fernandez et al. (1988) and developed a real-time SOM sensor intended to be recalibrated for each new soil catena, rather than for a large geographic area (such as several hundreds of square kilometers). The sensor consisted of compact transmitter and receiver modules that utilized light reflectance to measure SOM. Six or eight LEDs were arranged in an array around a photodiode to focus an intense beam of light on the soil surface directly below the photodiode. The position of the LEDs assured equal illumination of the sensed surface by each diode, minimizing specular reflectance. The field of view of the photodiode was constrained to the most intensely illuminated area of the soil surface and sensor height was 25 mm above the soil surface.

Laboratory tests using red (660 nm) LEDs as the light source on soil samples collected from five representative midwestern U.S. fields yielded strong correlations ($r^2 = 0.80$ to 0.98) for soils obtained within a single catena and prepared to a single

[2] A sequence of soils of about the same age, derived from similar parent material, and occurring under similar climatic conditions, but having different characteristics due to variation in relief and in drainage.

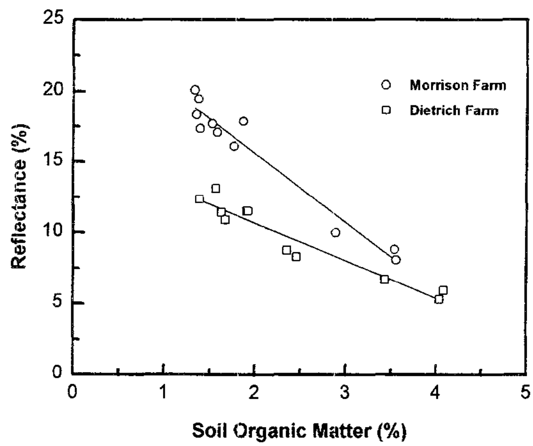

Fig. 1. Calibrations for the soil catena-dependent sensor for fine- and medium-textured soils from two representative Indiana farms.

moisture content (Table 1). Coefficients of determination (r^2) were greater for moist soils than air-dry soils. A linear relationship was found between light reflectance and SOM for two catenas, both having fine- and medium-textured soils (Fig. 1).

For field operation, the sensor was mounted to a tractor tool bar and operated below the soil surface to minimize the effect of soil moisture, soil surface roughness, plant cover, and crop residues on the sensor output. Field tests showed a curvilinear relationship between sensor output and SOM (r^2 = 0.84 to 0.95), with new calibrations developed for changes in travel speed or sensing depth (Shonk et al., 1991).

The sensor developed by Shonk et al. (1991) was licensed for commercial development, and used to control the rate of a granular herbicide formulation applied by a pneumatic metering system (McGrath et al., 1990). The probe was mounted to the front of a custom applicator truck and operated at a depth of 10 cm and speeds of up to 19 km h^{-1}. Soil samples were collected from each different soil catena to develop a specific sensor calibration curve. McGrath et al. (1990) noted that moisture and surface preparation significantly affected sensor output, and calibration should be carried out under conditions similar to those encountered at the time of chemical application. The variable rate application system satisfactorily applied herbicides in a number of field tests, and weed control was reported as excellent in all cases.

2.3. Multiple-wavelength sensing

The cooperative USDA-ARS/University of Illinois research project in optical sensing of soil properties has focused on developing an instrument designed to acquire NIR soil reflectance data at a number of narrow-band wavelengths. Although this type of instrument is more complex, more expensive, and less rugged than a single-band sensor, the additional reflectance information allowed the generation of accurate calibrations applicable to soils obtained from multiple soil catenas (Sudduth and Hummel, 1993a, b). The primary intended use of this sensor was to provide SOM data for control of a map-based herbicide application rate control system. In such a system, fields could be mapped with equipment shared among a number of producers or applicators. The SOM information could be used alone or combined with other data layers in a geographic information system (GIS) to generate herbicide application rate maps. The SOM information might also be used as a productivity indicator in the development of variable rate nitrogen application strategies since high SOM content soils, with their corresponding high soil moisture retention, are typically the highest producing portions of a field.

Extensive laboratory tests using a representative set of 30 Illinois mineral soils (Table 2) indicated that NIR data analyzed by partial least squares regression (PLSR) held the most promise for prediction of soil organic carbon content (Sudduth and Hummel, 1991). PLSR, a latent variable regression method, was used to reduce the set of collinear independent variables (reflectances) to a smaller set of orthogonal components which represented most of the variability in the original data and contained a reduced amount of random measurement noise (Martens and Naes, 1987). The analysis technique was evidentially able to minimize the effect of moisture, resulting in improved SOM prediction as compared to single-wavelength sensing. Excellent correlation [r^2 = 0.92, standard error of prediction (SEP) = 0.34% SOM] was obtained when the NIR data were smoothed to a 60-nm data point spacing and the wavelength range reduced to 1720–2380 nm, for a total of only 12 data points used. Similar correlations were obtained with a 40-nm data spacing and a slightly smaller wavelength range (Sudduth and Hummel, 1991).

A rugged, portable NIR spectrophotometer was developed to implement this prediction method, and laboratory and field tests were completed (Sudduth and Hummel, 1993a, b). The sensor used a circular variable filter (CVF) spinning at 5 Hz to sequentially provide monochromatic, chopped light from a broadband quartz-halogen source. A fiber optic bundle transmitted the monochromatic light to the soil surface, allowing remote mounting of the major portion of the sensor. A lead sulfide photodetector captured the energy diffusely reflected from the soil surface. The output from the detector was conditioned by an AC-coupled preamplifier and input to a PC through a 12-bit A/D converter. The effective sensing range was from 1630 to 2650 nm, on a 52-nm bandpass. The portable spectrophotometer predicted organic matter in the laboratory (Fig. 2), across a range of soil types and moisture contents, with a predictive capability (r^2 = 0.89, SEP = 0.40% SOM) approaching that of data obtained on the same soils with a research-grade spectrophotometer (Table 1). Field operation of the prototype sensor did not yield acceptable results (SEP = 0.91% SOM), due at least in part to errors introduced by the movement of soil past the sensor during the scanning process (Sudduth and Hummel, 1993b).

Additional laboratory tests of the NIR sensor with soils obtained from across the continental U.S. showed that acceptable SOM predictive capability could be maintained with a single calibration equation for soils from the lower U.S. Corn Belt — Illinois, Missouri, Indiana, and Ohio. Calibrations obtained for wider

Table 2
Organic matter, textural properties, and moisture content of 30 Illinois surface mineral soils

Soil name and textural class [a]	ID	Organic matter (%)	Textural properties			Mean moisture (%)	
			Sand (%)	Silt (%)	Clay (%)	1.5 MPa	0.033 MPa
Loamy sand							
Ade	1	0.77	86.5	7.3	6.2	1.52	4.08
Plainfield	2	1.02	83.7	12.7	3.6	0.97	6.04
Sparta	3	1.18	85.4	10.4	4.2	1.29	5.83
Maumee	4	1.79	84.1	7.6	8.3	1.99	5.73
Sandy loam							
Carmi	5	1.96	67.2	21.7	11.1	3.71	8.98
Loam							
Ambraw	6	2.18	48.0	29.2	22.0	8.16	14.63
Tice	11	1.71	25.8	50.0	24.2	8.61	18.09
Clay							
Jacob	7	3.47	3.8	33.6	62.6	22.59	34.63
Clay loam							
Proctor	8	1.41	25.6	47.1	27.3	7.25	17.98
Darwin	9	2.32	34.5	33.9	31.6	10.28	19.78
Silt loam							
Wynoose	10	1.62	6.3	79.0	14.7	5.01	20.91
Birkbeck	12	1.79	5.4	77.5	17.1	4.29	21.19
Shoals	13	1.27	27.8	59.6	12.6	3.94	18.58
Cisne	14	2.17	11.7	68.0	20.3	8.30	20.42
Bluford	15	1.32	20.3	66.9	12.8	3.66	19.40
Saybrook	16	2.18	12.7	62.8	24.5	7.92	20.78
Catlin	17	3.21	5.2	70.6	24.2	7.31	24.16
Saybrook	18	2.72	4.8	72.3	26.9	10.00	24.04
Cisne	19	2.68	11.5	66.3	22.2	9.66	21.47
Piopolis	22	2.65	4.1	68.8	27.1	7.23	25.31
Silty clay loam							
Flanagan	20	3.62	5.9	57.2	36.9	15.95	28.02
Jacob	21	1.93	9.4	65.8	24.8	9.42	25.91
Flanagan	23	3.17	6.3	67.1	26.6	8.64	22.59
Drummer	24	3.09	9.0	63.4	27.6	10.99	22.43
Flanagan	25	3.95	9.2	60.0	30.8	10.96	20.22
Drummer	26	5.01	8.7	61.0	30.3	12.52	22.58
Proctor	27	3.94	6.7	64.2	29.4	10.20	23.83
Flanagan	28	3.27	6.2	66.4	27.4	8.95	21.06
Drummer	29	3.85	12.6	55.9	31.5	12.44	25.13
Plano	30	3.13	7.9	65.6	26.5	8.76	19.85

[a] Textural classification and properties from Worner (1989).

geographic areas suffered from a significant decrease in accuracy (Table 1). A similar sensitivity analysis carried out on the soil reflectance database compiled by Stoner and Baumgardner (1981) confirmed these results (Sudduth et al., 1990).

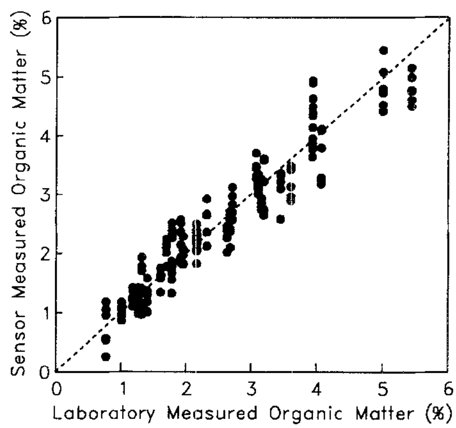

Fig. 2. Sensor versus laboratory measured SOM of 30 Illinois soils. Reflectance data were collected for soils at 0.033 and 1.5 MPa moisture tension levels, illustrating the sensor's capability to predict SOM over a broad range of soil moisture levels.

The prototype NIR sensor was redesigned for improved accuracy, faster data collection, and improved portability (Sudduth and Hummel, 1993c). As with the initial design (Sudduth and Hummel, 1993a), the revised spectrophotometer incorporated a broadband NIR source, CVF monochromator, and lead sulfide photodetector. The source and photodetector were unchanged from the initial design, while a 180° arc CVF replaced the original 90° arc CVF. This change reduced the optical bandwidth of the system at a given filter disk rotational speed, since the arc illuminated by the source would now represent a smaller wavelength span. The bandwidth reduction allowed flexibility to either acquire data more quickly with the same spectral resolution, as would be desirable in a field unit, or to collect data at the same speed with increased resolution, as might be desirable in a laboratory application. The sensing head was connected directly to the monochromator, rather than through the fiber-optic bundle used in the initial prototype. This direct connection was made to maximize throughput and improve the signal/noise ratio, especially at the longer wavelengths where the transmission characteristics of the fiber optics were a limiting factor in the initial prototype.

Electronic modifications were made to reduce the complexity and amount of off-line computation required to process the reflectance signal to usable form. Data acquisition was triggered by a 500 pulse rev^{-1} signal obtained from an encoder mounted to the CVF drive shaft. Thus, the photodetector output was digitized at fixed points in the rotation of the CVF, eliminating ambiguities due to shaft speed variations. This design allowed absolute reflectance to be calculated by direct point-by-point ratios of soil and ceramic reference disk reflectances, eliminating the interpolation procedure needed for the earlier prototype (Sudduth and Hummel, 1993a). The photodetector was provided with a constant-current excitation and a DC-coupled signal path to eliminate the need for time-consuming software correction as implemented in the previous AC-coupled signal path. Signal drift compensation was obtained by reading the photodetector output during the portion of the filter disk period when the input slit was not positioned over the CVF segment. A dedicated single-board computer was implemented for system calibration and optical performance evaluation (Sudduth and Hummel, 1993c).

The redesign of the portable NIR spectrophotometer resulted in improved ease of use and increased accuracy. Bandwidth of the revised instrument was 45 nm, wavelength instability was essentially eliminated, and reflectance data could be obtained on-line from the dedicated microprocessor within 10 s.

After optical performance was optimized and documented, the spectrophotometer was used for soil property estimation. Both a group of samples obtained from 30 surface soils and another set of samples collected from each of two soils at six depth increments were analyzed. The laboratory methods used to prepare and analyze the samples, the operation of the portable spectrophotometer, and the PLSR and stepwise multiple linear regression (SMLR) calibration procedures used to estimate SOM were discussed by Sudduth and Hummel (1993c).

Results of PLSR SOM estimation for the 30 surface soils ($r^2 = 0.84$, SEP = 0.43% SOM; Table 1) were comparable to results obtained with the previous prototype spectrophotometer. SMLR estimation using the maximum number of valid variables yielded slightly larger SOM prediction errors than did PLSR. SOM appeared to be more correlated with the general shape and level of the soil reflectance curve rather than with reflectance at specific wavelengths, causing better results to be obtained with the full-spectrum PLSR technique than with the SMLR technique.

PLSR and SMLR calibrations yielded similar SOM prediction errors through the soil profile (Sudduth and Hummel, 1993c). These results were more accurate than those obtained for the 30 surface soils. NIR estimation of SOM through the soil profile appears feasible, but additional work is needed to verify this relationship over a wider range of soils.

In a related project, Worner (1989) developed a portable spectrophotometer suitable for collection of multiple-wavelength visible/NIR reflectance data in the laboratory. Smith (1991) modified this spectrophotometer for improved performance and reliability, and used it to collect reflectance data on the same set of 30 Illinois soils used by other researchers (Pitts et al., 1986; Sudduth and Hummel, 1993b). Analysis of combined field capacity and wilting point moisture level data by SMLR yielded an r^2 of 0.61 and a SEP of 0.79% SOM (Table 1).

3. Sensing of soil moisture and CEC

Optical sensing of soil moisture using NIR takes advantage of the several water absorption bands in the NIR spectrum. Researchers have used data obtained at two (Christensen and Hummel, 1985; Kano et al., 1985) or three (Dalal and Henry, 1986) wavelengths, and have usually obtained good correlations ($r^2 > 0.9$) between soil moisture and reflectance.

Price and Gaultney (1993) developed a real-time sensor to measure soil moisture beneath the soil surface to aid in the placement of seeds at a depth where soil moisture was optimal for germination. The sensor was based on measuring the relative reflection of light from the soil surface illuminated by three sequentially pulsed laser diodes. The laser diodes emitted narrow spectrum pulses at 750, 810, and 840 nm. A maximum likelihood classifier algorithm was used to determine the most likely moisture content of the soil. In laboratory tests conducted on 29 soils encompassing three soil textures (loam, silt loam, and silty clay loam) and five soil moisture tensions, the sensor was able to classify 82% of the samples correctly into moist (0.01, 0.03 or 0.05 MPa) or dry (0.1 or 1.5 MPa) categories. In field tests, at speeds of 2–3 km h^{-1}, the sensor correctly classified 82% of the soil samples. As long as soil type did not vary greatly, the sensor could estimate soil moisture with sufficient accuracy for planting depth control, where the objective is locating the drying front where soil moisture transitions from dry to moist occur in a relatively small depth increment.

Since PLSR techniques were able to minimize the effects of soil moisture on SOM prediction, it also seemed reasonable to investigate the use of the technique to remove the effects of SOM on NIR reflectance spectra and attempt to predict total soil moisture. Using PLSR techniques, the portable NIR spectrophotometer (Sudduth and Hummel, 1993a) was evaluated for estimating soil moisture. The spectral reflectance data obtained in the laboratory (Sudduth and Hummel, 1993b) were correlated with laboratory determined gravimetric moisture for the 30 Illinois soils. Moisture content was predicted with a SEP of 1.88% ($r^2 = 0.94$) for a dataset including moisture tensions of 0.033, 0.33, and 1.5 MPa, and air-dry soil (Fig. 3). In terms of the coefficient of variation (CV), the prediction of soil moisture was more accurate than the prediction of SOM.

CEC is somewhat correlated to soil texture and SOM (Brady, 1984). The NIR dataset for the 30 Illinois soils was used to assess the sensor's prediction capability for this soil property. The 0.033 and 1.5 MPa moisture datasets were combined to

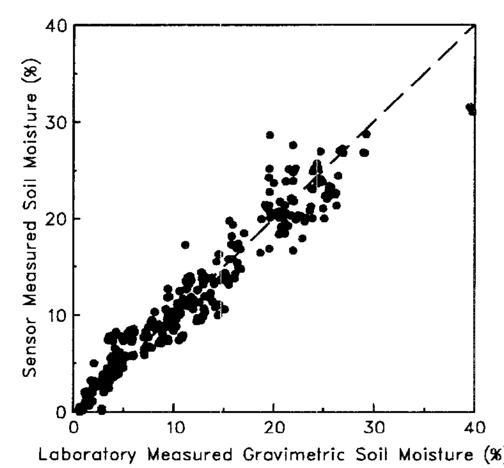

Fig. 3. Sensor predicted versus laboratory measured moisture content of 30 Illinois soils. Soil samples having moisture levels of air-dry and 0.033, 0.33, and 1.5 MPa moisture tension were included in the test.

increase the number of replications, since CEC is unaffected by soil moisture. A CEC prediction yielded a SEP of 3.59 mEq $(100\ g)^{-1}$ for the combined 0.033 and 1.5 MPa moisture tension dataset, illustrating the sensor's prediction capability over the broad range of soil moistures that might be encountered during field operations. Again, in terms of the CV, the prediction of CEC was more accurate than the prediction of SOM.

4. Sensing of other soil properties

4.1. Nitrate sensing

Over-use of nitrogen fertilizer is costly to the producer, and can adversely affect the environment if the excess is leached into surface- or ground-waters. Customizing the inputs of nitrogen fertilizer to every part of a field could optimize yield potential by minimizing input costs, optimizing yields, and helping to protect the environment. Several studies have shown that ion selective electrodes can be used to measure soil nitrates. A hand-held nitrate meter is commercially available from Spectrum Technologies, Inc.[3] (Plainfield, IL, USA), that provides a reading in a matter of minutes. Adsett and Zoerb (1991) reported on research on near real-time nitrate sensing using ion selective electrodes. An automated field monitoring system consisting of a soil sampler, nitrate extraction unit, flow cell, and controller were laboratory and field tested. The nitrate extraction time and methodology were limiting factors in the system, and additional research was planned to improve the mixing and extraction phases.

ISFETs have several advantages over ion selective electrodes such as small dimensions, low output impedance, high signal/noise ratio, fast response and the ability to integrate several sensors on a single chip. However, ISFETs have the disadvantage of greater long-term drift and hysteresis than ion selective electrodes. Although these are potential problems in static measurements, the use of a dynamic measurement system such as flow injection analysis minimizes the effects of drift and hysteresis, and exploits the specific properties of ISFETs. The ability to use small sample volumes and sense multiple species simultaneously makes the ISFET an attractive sensor for the development of a real-time soil nutrient sensing system.

Birrell and Hummel (1993) investigated the use of ISFETs to measure soil nitrate. A chip with four integrated ISFETs was tested in a flow injection system using four different flowrates ranging from 0.04 to 0.19 ml s^{-1}, five sample injection times ranging from 0.25 to 2 s, and three washout times ranging from 0.75 to 2 s. The baseline solution was pumped through the flowcell, and the test solution was injected into the flow stream. When injecting standard nitrate solutions, the correlation coefficients of a linear regression of the signal peak height against the logarithm (base 10) of the nitrate concentration were within the range 0.89–0.99,

[3] Mention of a trade name, proprietary product, or specific equipment does not constitute a guarantee or warranty by the USDA-ARS or E.I. du Pont de Nemours & Co. and does not imply the approval of the named product to the exclusion of other products that may be suitable.

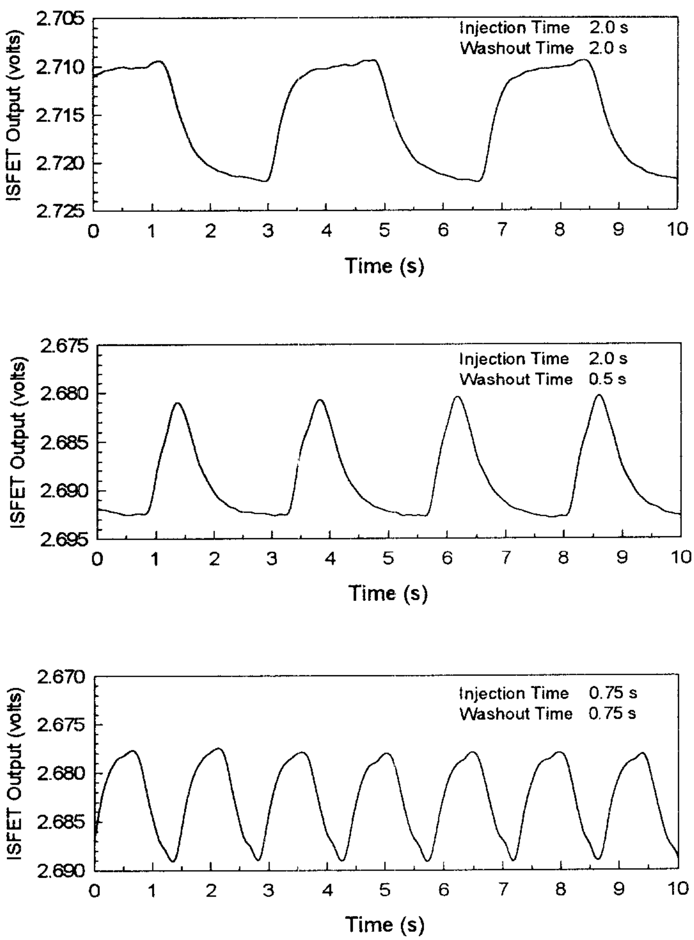

Fig. 4. Effect of flowcell sample injection and washout times on the ISFET signal with $2(10)^{-4}$ M $NaNO_3$ at 0.09 ml s^{-1} flowrate.

except for the lowest flowrate which was in the range 0.72–0.99. Typical ISFET responses (Fig. 4) illustrate the effect of the ratio of injection time to washout time, and the rapid response of the ISFET to a change in input. Baseline drift is evident, but not problematic, as long as signal peak height relative to the baseline is used for each injection cycle. A cycle period of 1.5 s (0.5 s injection, 1.0 s washout time) seemed possible. The major problem encountered was inconsistent opening and closing of the injection valve, and an improvement in valve operation should increase the precision of the system.

4.2. Sensing of depth-to-claypan

Claypan soils, which have a dense, clay-rich layer, cover large areas of midwestern U.S. Within these soils, crop production is often limited by the thickness of the

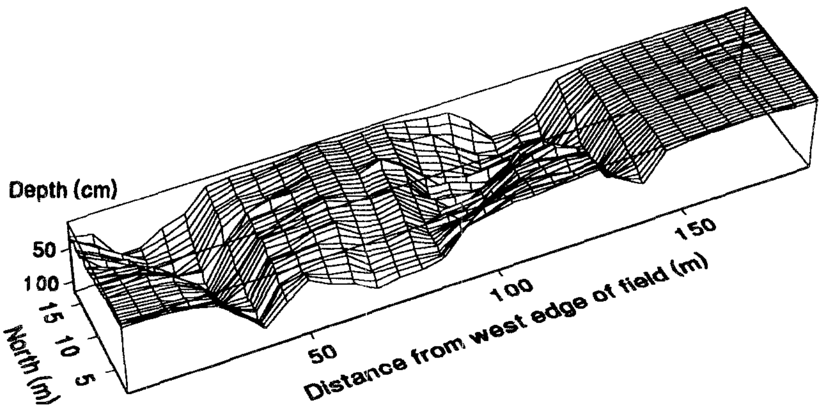

Fig. 5. The upper surface of the claypan in a 0.35-ha research plot, with depth below the soil surface estimated by electromagnetic induction, shows two buried channels crossing the plot.

topsoil (or depth-to-claypan), and variability in this parameter must be considered in development of site-specific nutrient management strategies. Standard practice for quantifying claypan depth and characteristics involves use of a manual or powered soil probe at each sampling location, a slow and laborious process. Consequently, mapping of claypan depth has not been practical for production agriculture purposes. In order to quantify claypan depth variations over a large area, an automated, preferably non-invasive, measurement means is required.

Several automated methods for estimating depth-to-claypan were explored (Sudduth and Kitchen, 1993), including mechanical impedance measurement, ground penetrating radar, and EM methods of soil conductivity measurement. Of these, the EM measurements made with a hand-held commercially available sensor (Model EM38, Geonics Ltd., Mississauga, Ont.) have provided the best results. A transect was established in a large research plot where rapid spatial variations in depth-to-claypan had been detected by soil probing, and EM measurements were successfully regressed ($r^2 = 0.81$) on soil probe measurements. EM data were also collected on a 3×6 m grid over the entire 0.35-ha plot, and the calibration obtained on the probed transect was used to map the EM-estimated upper surface of the claypan (Sudduth and Kitchen, 1993). In these data, two buried channels can be observed crossing the plot (Fig. 5); features confirmed by soil probing and by aerial photographs taken during the dry 1992 growing season which showed increased crop vigor in the channel areas.

5. Conclusions

SSCM requires the collection, coordination, and analysis of massive quantities of data. A large portion of those data will be collected by electronic instrumentation operating within each field. Information on soil property variations, often obtained today by laboratory analysis of manually collected soil samples, will be streamlined by the use of sensing technologies currently under development.

Considerable progress has been made in the development of sensors for use in field production systems. Two SOM sensors, a single-wavelength, soil catena-dependent sensor (Shonk et al., 1991) and a multiple-wavelength, catena-independent sensor (Sudduth and Hummel, 1993a, b) have both been licensed for commercial development. Either approach seems feasible, and each has advantages and disadvantages. The single-wavelength sensor requires user acceptance of the need to recalibrate the sensor for new soil catenas and moisture levels, but is relatively inexpensive and rugged. The multiple-wavelength sensor has been calibrated for a wide geographic range and a range of soil moistures, and can also be used to sense soil moisture and CEC, but uses more complex technology. A simpler, less expensive sensor that can classify soils according to soil moisture has also been developed. Sensors for other soil parameters are being sought, and progress has been reported on nutrient and depth-to-claypan sensing.

To date, sensor-based estimates of soil properties are generally less accurate than those obtained by laboratory analyses. However, real-time sensing allows much more data to be obtained with the same amount of effort, and these multiple points can be averaged to obtain improved prediction accuracy. Also, for those sensors which have been calibrated for a wide range of soil property variations, the data obtained within a single application could reasonably be expected to show smaller errors.

As consumers' concerns about the impact of agricultural inputs on the environment accelerate the demand for sensors and sensing systems, research and development in both the public and private sectors should expand. Future research and development efforts will undoubtedly improve the technology to provide more accurate sensors and improved control of agricultural inputs, and reduced environmental impact.

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