GEOGRAPHIC OPERATING RANGE EVALUATION
OF A NIR SOIL SENSOR

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ABSTRACT. *A previously developed prototype soil sensor which used near infrared (NIR) reflectance techniques was tested in the laboratory. The test set of soils included 30 Illinois soils and another 33 soils collected from across the continental U.S., all prepared at soil moisture tensions ranging from 1.5 MPa (wilting point) to 0.033 MPa (field capacity). As the geographic range represented by the included samples was increased, the predictions of organic carbon, cation exchange capacity, and soil moisture became less accurate. Calibrations obtained with soils from several states of the lower Corn Belt (Illinois, Missouri, Indiana, and Ohio) were only slightly less predictive of soil organic carbon than calibrations developed for the Illinois soils alone. Extension of the geographic range westward or northward from this area reduced the organic carbon prediction accuracy to an unacceptable level.* **Keywords.** *Organic matter, Soil moisture, Spectrophotometry, Instrumentation, Precision agriculture.*

Cropping system management is generally practiced on a field basis, with fertilizers, pesticides, and seed applied at a uniform rate over the whole field. Actual needs for these inputs can commonly vary by a factor of two or more over the field so that a uniform rate based on the spatially averaged requirements is too high for some areas and too low for others. Over-application results in increased production costs and may also cause environmental damage due to excess chemical contaminating surface water or groundwater. Under-application can result in decreased yields due to poor control of pests and inadequate fertility levels. Ideally, application rates should be adjusted to meet the requirements for each part of the field.

With many soil-applied herbicides, the application rate required for effective weed control increases as soil organic carbon content (or organic matter content*) increases, due to adsorption of the herbicide on the cation exchange complex of the organic matter. Meggitt (1970) reported that a linear increase in herbicide dose was required to maintain weed control as organic matter increased up to 15%, when using compounds such as *s*-triazines, thiocarbamates, and pyridazinones. Variations in organic matter of almost 100% were observed along an 80-m transect in a flat, apparently uniform field in central Illinois (Sudduth and Hummel,

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* In the context of this research, soil organic matter content is defined as 1.72 times the organic carbon content.

1993b); larger variations might be expected in areas with more variable topography or over longer distances. With this level of variability, significant opportunity exists for cost savings through input optimization of soil-applied herbicides based on soil organic matter content.

Higher organic matter content soils are generally less reflective than soils with lower organic matter contents. Researchers have developed several optical soil organic matter sensors based on this reflectance difference, with varying degrees of success. Other soil variables important in spatially variable cropping system management have also been sensed on the basis of soil reflectance properties. These include nutrient level (for control of fertilizer application rate), cation exchange capacity (soil-applied herbicide rate control), and soil moisture (seeding depth control).

Sudduth and Hummel (1993a,b) developed a soil property sensor based on near infrared (NIR) reflectance and tested it in the laboratory and field with representative Illinois soils. This study, an extension of that work, focused on developing and evaluating NIR-based estimations of soil organic carbon, soil moisture, and cation exchange capacity (CEC) for a suite of soils obtained over a wider geographic area.

LITERATURE REVIEW

Several researchers have developed optical soil organic matter (SOM) sensors designed to be used as a control input for variable-rate herbicide application (Krishnan et al., 1980; Griffis, 1985; Pitts et al., 1986; Gunsaulis et al., 1991; Shonk et al., 1991). A general review of past progress in soil organic matter sensing research was given by Sudduth et al. (1991).

In development of the sensor used in this study, Sudduth and Hummel conducted extensive laboratory tests using a representative set of 30 Illinois mineral soils. These tests indicated that NIR data analyzed by partial least squares regression (PLSR) held the most promise for prediction of soil organic carbon content. 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 analytical technique was evidently 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 to 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 computer through a 12-bit analog-to-digital 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, 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. 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).

Soil properties other than organic carbon also have an effect on reflectance characteristics, e.g., moisture, particle size, and iron content (Baumgardner et al., 1985). Sudduth and Hummel (1993b) predicted soil moisture and cation exchange capacity for 30 Illinois soils using NIR reflectance techniques. Other researchers have also predicted soil moisture content using NIR reflectance methods (Kano et al., 1985; Christensen and Hummel, 1985; Dalal and Henry, 1986).

In all previous research, calibration of soil organic matter sensors has been accomplished either within a given soil catena[†] (Shonk et al., 1991) or for a representative set of soils from a single state (Krishnan et al., 1980; Griffis, 1985; Pitts et al., 1986; Gunsaulis et al., 1991; Sudduth and Hummel, 1993b). However, investigators interested in soil classification (as opposed to sensing for herbicide application rate control) have investigated correlations between organic matter and reflectance or color properties for a wider range of soils. McKeague et al. (1971) correlated Munsell value with organic matter content of the surface horizons of 115 soils collected in various parts of

Canada, obtaining an r^2 of 0.36. Stoner and Baumgardner (1980) correlated average reflectance in 100 nm and wider spectral bands with physical and chemical properties of 481 soils collected from across the continental U.S. They obtained an r^2 of 0.46 when considering all 481 soils, and a maximum r^2 of 0.66 when analyzing correlations separately by climatic zone.

OBJECTIVES

The overall objective of this research was to investigate the effect of geographic range on the accuracy of soil property estimation by NIR reflectance. Specific objectives were to:

1. Evaluate organic carbon calibrations of the sensor developed by Sudduth and Hummel (1993a) when using soils obtained from an expanded geographic range, as compared to the previous work which used only Illinois soils.
2. Investigate NIR estimation of soil moisture content and CEC over an expanded geographic range using data from the same sensor.
3. Evaluate the effect of increasing geographic range on organic carbon estimations obtained with an independent set of soil reflectance data, for comparison to sensor results.

MATERIALS AND METHODS

Two sets of data were used to evaluate the geographic range of organic carbon prediction. One set of data was derived from surface samples of 33 soils collected for the USDA Water Erosion Prediction Project (WEPP). The other data were obtained from the Laboratory for Applications of Remote Sensing (LARS) at Purdue University. These LARS soil property and laboratory reflectance data for 481 soil samples collected within the continental U.S. were obtained and analyzed by Stoner and Baumgardner (1980, 1981). Soil moisture content and CEC estimations based upon WEPP soil reflectance data were also evaluated.

WEPP SOILS

The soils selected by the WEPP investigators were chosen to span a broad range of soil physical, chemical, biological, and mineralogical properties; to be subject to erosion; and to be of regional or national importance (Alberts et al., 1987). At an erosion study plot within each chosen soil, three types of soil samples were collected for analysis: (1) pedon samples from each soil horizon, (2) bulk surface samples, and (3) undisturbed cores. Physical and chemical properties of the pedon samples were measured at the USDA Natural Resources Conservation Service National Soil Survey Laboratory (NRCS NSSL). These analyses included particle size, moisture tension, cation exchange capacity, organic carbon, total carbon, and total nitrogen (West et al., 1987).

Surface soil samples were collected at 16 sites within each plot, on a 4-row × 4-column grid with approximately 2 m between samples. The four samples in each column were combined, creating four composite samples to represent the variability in surface soil characteristics (West et al., 1987). Subsamples of these four composite surface samples for each of 33 soils (table 1) were available for use in this project.

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† 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.

Table 1. Textural class and characteristics of each of 33 soils collected for the USDA Water Erosion Prediction Project (WEPP)

State	Soil Name	Textural Class*	Organic Carbon† (%)				CEC* (mEq/ 100g)	Soil Moisture*‡ (%)	
			Site 1	Site 2	Site 3	Site 4		1.5 MPa	0.033 MPa
Calif.	Academy	Loam	0.38	0.40	0.35	0.40	5.3	3.5	8.6
	Los Banos	Clay loam	1.78	1.85	1.83	1.88	38.8	19.1	28.4
	Whitney	Sandy loam	0.28	0.27	0.19	0.23	3.4	2.6	6.7
Ga.	Bonifay	Sand	0.27	0.26	0.21	0.22	1.8	1.1	4.8
	Cecil	Sandy clay loam	0.65	0.62	0.78	0.73	3.5	8.3	14.2
	Hiwassee	Sandy loam	0.63	0.57	0.61	0.56	4.4	6.4	13.8
	Tifton	Loamy sand	0.46	0.48	0.50	0.47	2.1	2.1	6.0
Idaho	Portneuf	Silt loam	0.72	0.72	0.72	0.72	12.6	8.3	24.7
Ind.	Lewisburg	Clay loam	1.06	0.89	0.98	0.86	12.5	11.3	17.3
	Miami	Silt loam	0.86	0.77	0.75	0.86	13.3	10.0	22.7
Md.	Frederick	Gravelly silt	1.21	1.17	1.27	1.32	8.4	6.8	26.6
	Manor	Loam	0.49	0.77	0.88	0.94	11.9	11.7	25.9
	Opequon	Silt loam	1.59	1.57	1.61	1.54	12.9	14.2	25.3
Maine	Caribou	Gravelly loam	1.99	1.84	1.93	1.61	12.8	8.9	26.9
Minn.	Barnes	Loam	1.64	1.71	1.69	1.82	19.5	9.3	21.8
	Sverdrup	Sandy loam	0.75	0.73	1.28	0.91	11.0	5.4	13.4
Mo.	Mexico	Silt loam	1.54	1.50	1.58	1.56	21.3	11.5	32.1
Miss.	Grenada	Silt loam	1.01	0.85	0.85	0.99	12.0	10.9	23.5
Mont.	Zahl	Loam	1.52	1.61	1.71	1.79	20.0	11.0	20.3
N.C.	Gaston	Clay loam	1.07	1.04	1.07	1.08	9.2	14.8	22.0
N.Dak.	Barnes	Loam	2.52	2.43	2.33	2.67	22.8	12.7	28.5
	Williams	Loam	1.75	1.75	1.75	1.75	22.6	11.9	23.5
Nebr.	Hersh	Fine sandy loam	0.53	0.33	0.32	0.36	7.2	4.3	12.7
	Keith	Loam	0.98	0.81	0.96	0.91	18.3	10.3	19.6
	Sharpsburg	Silty clay loam	1.75	1.81	1.74	1.83	29.4	17.4	27.0
N.Y.	Collamer	Silt loam	1.06	0.99	0.98	1.00	8.9	6.9	24.7
Ohio	Miamian	Silt loam	3.19	3.13	2.97	2.62	14.4	10.9	17.8
Okla.	Woodward	Fine sandy loam	0.76	0.69	0.68	0.76	12.6	7.4	14.4
S.Dak.	Pierre	Clay	1.40	1.37	1.44	1.40	34.9	19.1	26.6
Tex.	Amarillo	Fine sandy loam	0.14	0.18	0.14	0.16	5.1	3.4	7.3
	Heiden	Silty clay	1.36	1.36	1.36	1.36	33.3	18.9	28.8
Wash.	Nansene	Silt loam	1.23	1.30	1.32	1.31	15.1	7.3	34.0
	Palouse	Silt loam	1.18	1.35	1.28	1.36	19.6	9.0	26.3

* Determined by pedon sample analysis at USDA-NRCS National Soil Survey Laboratory.
† Organic carbon content from analysis of four surface samples collected for each soil.
‡ Soil moisture tension of 1.5 MPa is termed "wilting point", and 0.033 MPa is termed "field capacity".

Soil from each of the 132 samples (4 composite samples of each of 33 soils) was oven-dried, hand-cleaned to remove foreign material, and crushed to pass through a 2 mm sieve. Approximately 150 g was prepared by adding by volume the amount of water required to reach the 1.5 MPa (wilting point) moisture tension level as determined by the pedon analysis at the USDA-NRCS NSSL (table 1). Water was added to a second subsample to reach the 0.033 MPa (field capacity) moisture tension level. The samples were placed in plastic bags and manipulated by hand to distribute the added water. They were then refrigerated for at least 5 days to allow time for the added moisture to equilibrate with the soil. Total carbon was determined by dry combustion of duplicate samples in an induction furnace. Each soil was tested for the presence of carbonates, to indicate if total carbon was equivalent to organic carbon. Organic matter content was then determined in the standard manner as 1.72 times the organic carbon content.

Soil samples were analyzed with the NIR laboratory sensor (Sudduth and Hummel, 1993a) in two groups. The first group consisted of three replications of the first composite sample of each soil at each of the two moisture tension levels (n = 198). The second group consisted of two replications of the three remaining composite samples of each soil at each of the two moisture tension levels

(n = 396). The order of data collection was randomized within each replication.

Reflectance data were obtained in the laboratory on prepared samples, using the same procedures reported in the previous study with 30 Illinois soils (Sudduth and Hummel, 1993b). These data were averaged to a 40 nm bandpass and transformed from reflectance to optical density [OD, defined as $\log_{10}$ (1/reflectance)]. The data covered center wavelengths from 1640 nm to 2640 nm, for a total of 26 processed reflectance readings in each spectrum. Correlation of soil spectral OD data and chemical/physical property data was accomplished using partial least squares regression (PLSR). The 0.033 MPa and 1.5 MPa moisture tension data were analyzed as a group to bracket the moisture conditions likely to be encountered in field operation.

LARS SOILS

The LARS soil database used by Stoner and Baumgardner (1980, 1981) was obtained from Purdue University. This database included information on surface soil samples of 242 U.S. soil series. For 239 of these series, duplicate samples were obtained from another site 1 to 30 km distant from the primary sampling location, resulting in 481 total samples. The soil series were selected at random within climatic strata (defined as a temperature regime — moisture zone combination) from 1,300 U.S. benchmark soils. The samples came from 17 continental

U.S. climatic zones and included soils from 28 suborders of 9 soil orders (Stoner and Baumgardner, 1981).

The soil fraction passing a 2 mm sieve was used for laboratory determination of chemical, physical, and reflectance properties, including Walkley-Black organic carbon. Stoner and Baumgardner (1981) obtained reflectance measurements using a spectroradiometer, on soil samples equilibrated to 0.010 MPa moisture tension. Spectral readings were taken every 10 nm over the range from 520 nm to 2320 nm. Six spectral scans on each soil sample were averaged to generate the mean scan stored in the LARS database (Stoner and Baumgardner, 1980). Data for 84 soil series from 12 Midwestern states (Iowa, Illinois, Indiana, Kansas, Michigan, Minnesota, Missouri, North Dakota, Nebraska, Ohio, South Dakota, and Wisconsin) were extracted from the LARS database, averaged to a 60 nm spacing and transformed from reflectance to OD. These data covered a range of center wavelengths from 595 nm to 2295 nm. Correlation of spectral information and Walkley-Black organic carbon was accomplished using PLSR applied to various subsets of the data.

RESULTS AND DISCUSSION
WEPP SOILS

Soil organic carbon (table 1) for the four surface samples of the 33 soils ranged from 0.14% to 3.19%, with a standard deviation of 0.65% organic carbon. Inorganic carbon was detected in three of the test soils: Portneuf Silt Loam (Idaho), Williams Loam (N.Dak.), and Heiden Silty Clay (Tex.). For these soils, the entries in table 1 were those determined by analysis of pedon samples at the USDA-NRCS NSSL. Entries for the other soils were determined by dry combustion of subsamples of the four spatial samples of each soil. The within-soil standard deviation averaged 0.06% organic carbon, with a maximum of 0.22% organic carbon, indicating the presence of some heterogeneity among the four samples of each soil. With this amount of variability, care should be taken in correlating soil properties determined by the USDA-NRCS NSSL with spectral characteristics. These properties were determined on a characteristic pedon from within the sampling site, but could vary from the properties actually present in each of the four surface samples.

A sequence of PLSR analyses included data from the 30 Illinois soils previously analyzed by Sudduth and Hummel (1993b) and selected subsets of the data collected on the WEPP soils. As the geographic range represented by the included samples was increased, the predictive capability of the regression decreased (table 2). Of the measures of fit used in table 2, RPD, the ratio of standard deviation to standard error of prediction (SEP), is the most instructive in comparing results on datasets containing differing degrees of variability. Williams (1987) reported that an RPD of 3 or higher would indicate accurate predictions in a dataset with little variance (standard deviation = 0.5) in the constituent being measured, with a higher RPD required for data with more variability.

The organic carbon analyses on WEPP soil data could be segmented into three accuracy classes (fig. 1). From highest accuracy to lowest they were:

1. Data from the 30 Illinois soils analyzed by Sudduth and Hummel (1993b).

Table 2. Summary of partial least squares regression results using WEPP and Illinois soils for determining the effect of geographic range on prediction of organic carbon with the NIR soil sensor

Geographic Range and (No. of Soils)	No. of* Valid Factors	r^2	SEC†	SEP‡	RPD§
Ill. (30)	17‖	0.89	0.22	0.23	2.9
Ill., Mo., Ind. (33)	13	0.87	0.24	0.25	2.6
Ill., Mo., Ind., Ohio (34)	18	0.86	0.26	0.28	2.5
Ill., Mo., Ind., Ohio, Minn. (36)	13	0.75	0.35	0.37	1.9
North-central U.S. (43)#	16‖	0.72	0.36	0.37	1.8
Continental U.S. (63)	10	0.67	0.40	0.40	1.7
WEPP Soils Only					
Mo., Ind., Ohio, Minn. (6)	8	0.85	0.33	0.41	2.0
North-central U.S. (13)**	14	0.72	0.37	0.42	1.7
Continental U.S. (33)	21	0.73	0.34	0.36	1.8

* The maximum number of valid PLSR factors as determined by cross-validation.
† SEC (standard error of calibration) is the standard error of the estimate in the calibration data, in percent organic carbon.
‡ SEP (standard error of prediction) is the standard error of the estimate in the validation data, in percent organic carbon.
§ RPD is the ratio of standard deviation to SEP.
‖ Maximum number of factors which could be extracted by the program, although additional factors may be valid. Results presented are based on this number of factors.
Includes soils from Ill., Mo., Ind., Ohio, Minn., Nebr., S.Dak., N.Dak., and Mont.
** Includes soils from Mo., Ind., Ohio, Minn., Nebr., S.Dak., N.Dak., and Mont.

2. Data from the lower Corn Belt. Similar prediction accuracies were obtained with (a) data from Ill., Mo., and Ind., and (b) data from Ill., Mo., Ind., and Ohio.
3. Data from a wider geographic range. Similar predictions were obtained with (a) data from Ill., Mo., Ind., Ohio, and Minn., (b) data from the North-central U.S., and (c) data from all 33 WEPP soils covering the continental U.S.

Separate analyses were completed for the WEPP data without including the 30 Illinois soils (table 2). Again, the (Mo., Ind., Ohio, and Minn.) dataset, the North-central U.S. dataset, and the continental U.S. dataset were similar in terms of prediction accuracies. The smaller datasets (Mo. and Ind.) and (Mo., Ind., and Ohio) were not analyzed as separate entities due to an insufficient number of observations.

Another analysis investigated the prediction degradation caused by including all four spatial variability sampling sites for each WEPP soil (all other analyses only included data from one site for each soil, due to dataset size limitations in the commercial software used for analysis). All 33 WEPP soils were analyzed as a group, yielding an SEP of 0.41% carbon and an RPD of 1.6. These results were less predictive than the results obtained with the same data but only one sampling site per soil (SEP = 0.36, RPD = 1.8). However, due to dataset size constraints in the analysis software, only 8 factors were extracted from the multiple site data as compared to 21 valid factors for the single site data. Differences in prediction accuracies would have been less if more factors could have been obtained for the multiple site data.

The WEPP soils dataset was also analyzed for prediction of cation exchange capacity (CEC) and soil
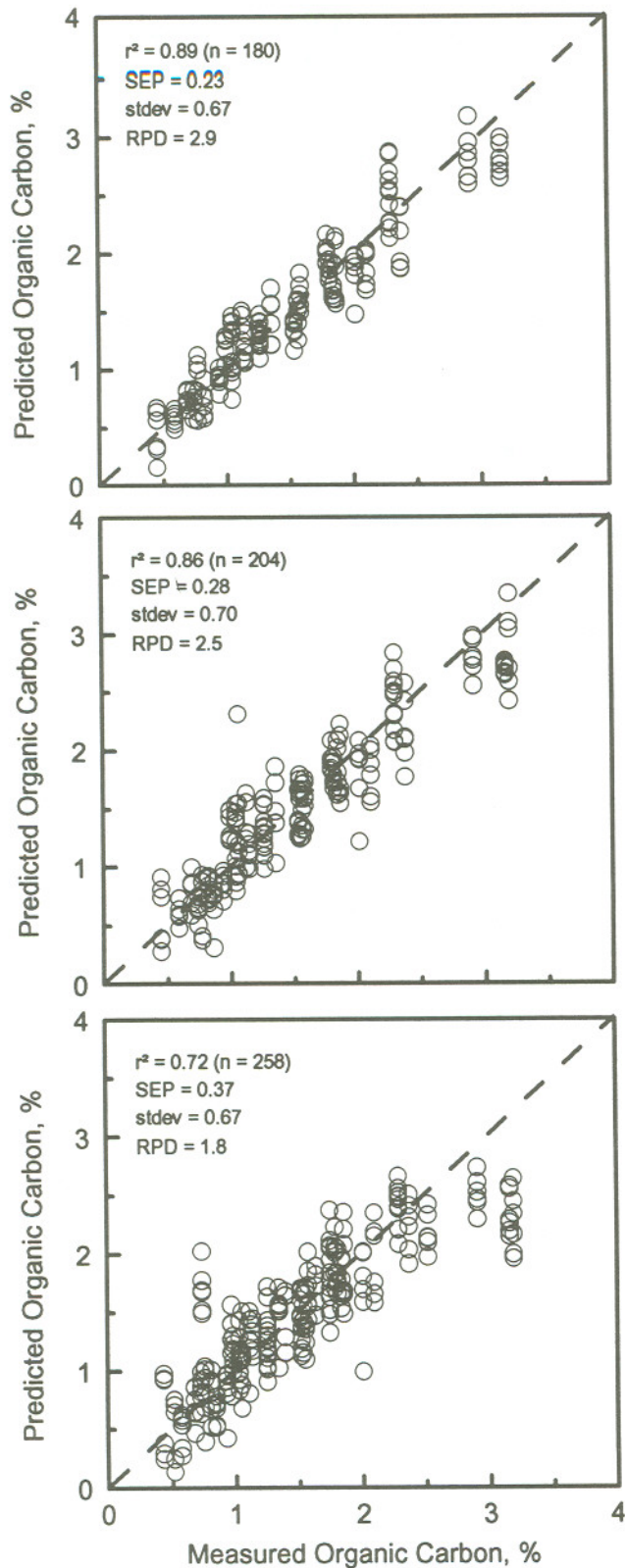
Figure 1–Comparison of organic carbon predictions from each of three accuracy classes. From top to bottom, predictions are for (a) 30 Illinois soils; (b) 34 soils from Ill., Mo., Ind., and Ohio; and (c) 43 soils from the North-central U.S.

Table 3. Summary of partial least squares regression results using WEPP and Illinois soils for determining the effect of geographic range on prediction of cation exchange capacity (CEC) and soil moisture with the NIR soil sensor

Geographic Range and (No. of Soils)	No. of* Valid Factors	r^2	SEC†	SEP‡	RPD§
Cation Exchange Capacity (CEC)					
Ill. (30)	11	0.86	3.45	3.59	2.4
Mo., Ind, Ohio, Minn. (6)	8	0.63	2.34	2.79	1.4
North-central U.S. (13)‖	9	0.84	2.95	3.19	2.3
Continental U.S. (33)	14	0.85	3.61	3.76	2.5
Soil Moisture					
Ill. (30)	10	0.97	1.48	1.59	5.1
Mo., Ind., Ohio, Minn. (6)	9	0.96	1.36	1.98	3.5
North-central U.S. (13)‖	7	0.85	2.55	2.87	2.3
Continental U.S. (33)	21	0.80	3.49	3.92	2.0

* The maximum number of valid PLSR factors as determined by cross-validation.
† SEC (standard error of calibration) is the standard error of the estimate in the calibration data, in units of mEq/100g (for CEC) or percent water.
‡ SEP (standard error of prediction) is the standard error of the estimate in the validation data, in units of mEq/100g (for CEC) or percent water.
§ RPD is the ratio of standard deviation to SEP.
‖ Includes soils from Mo., Ind., Ohio, Minn., Nebr., S.Dak., N.Dak., and Mont.

analyses, but are presented for comparison. As with organic carbon, predictions of soil moisture content were significantly less precise when the geographic range was increased. Except for one outlier, CEC prediction accuracies remained relatively constant with increasing geographic range. This relative robustness of CEC estimations with respect to geographic range indicates that variable-rate herbicide application based on sensor-derived CEC data may warrant further investigation.

LARS SOILS

Organic carbon prediction with the LARS soil data (table 4) showed trends similar to those found with the WEPP soils. Again, data obtained from states in the lower Corn Belt

Table 4. Summary of partial least squares regression results using LARS soils for determining the effect of geographic range on prediction of organic carbon using spectral reflectance data

Geographic Range and (No. of Soils)	No. of* Valid Factors	r^2	SEC†	SEP‡	RPD§
Ill., Mo., Ind., Ohio (34)	7	0.90	0.29	0.43	2.2
Ill., Mo., Ind. Ohio, Iowa (48)	9	0.90	0.26	0.38	2.3
Ill., Mo., Ind., Ohio, Iowa, MN (78)	9	0.89	0.39	0.58	2.0
Ill., Mo., Ind., Ohio, Minn., Wisc., Mich. (107)	9	0.82	0.50	0.65	1.8
North-central U.S. (164)‖	7	0.72	0.63	0.71	1.7

* The maximum number of valid PLSR factors as determined by cross-validation.
† SEC (standard error of calibration) is the standard error of the estimate in the calibration data, in percent organic carbon.
‡ SEP (standard error of prediction) is the standard error of the estimate in the validation data, in percent organic carbon.
§ RPD is the ratio of standard deviation to SEP.
‖ Includes soils from Ill., Mo., Ind., Ohio, Iowa, Minn., Wisc., Mich., Kans., Nebr., S.Dak., and N.Dak.

moisture content (table 3). Data from the 30 Illinois soils were not combined with the WEPP soils data for these

(Ill., Mo., Ind., Ohio, and Iowa) were most predictive of organic carbon. Prediction accuracy was reduced by extending the range north to include Minn., Wisc., and Mich., and further reduced by extending the range west to include Kans., Nebr., S.Dak., and N.Dak. The complete continental U.S. group of LARS soils was not analyzed, due to dataset size limitations in the PLSR analysis program.

Analysis of the LARS data was useful to confirm the general effects of geographic range on prediction accuracy. However, direct comparison of the LARS and WEPP datasets was not possible due to differences between the two datasets. Shortcomings of the LARS data included more noise, reduced sensing range at higher wavelengths, data at only one moisture tension level (0.01 MPa), and no replication of reflectance spectra. On the other hand, the LARS sensing range was extended at lower wavelengths, and the duplicate samples of most soils collected at a 1 km or greater spacing provided more realistic spatial variability information.

Based on the results obtained with the WEPP and LARS datasets, it was apparent that organic carbon prediction by NIR reflectance would be less accurate for wider geographic ranges. Analyses which included soils from more than one temperature/moisture regime yielded less accurate predictions than analyses where all soils were from the same climatic regime. All WEPP soil predictions generated for the lower Corn Belt (Mo., Ill., Ind., Ohio, and Iowa) yielded an SEP of less than 0.29% organic carbon (0.50% organic matter) and could be considered acceptable. However, additional soils from that geographical area should be analyzed to ensure that acceptable predictions could be maintained for the range of agriculturally important soils present in each state.

CONCLUSIONS

The geographic range over which a set of soil samples was obtained affected the accuracy of NIR predictions of organic carbon, CEC, and soil moisture. Specifically:

1. Predictions of organic carbon and soil moisture became less accurate as soil samples from a wider geographic range were considered. Estimations of CEC, a parameter which is also related to required herbicide application rate, exhibited a relatively constant accuracy.
2. Acceptable organic carbon prediction accuracies were retained when NIR data from the lower Corn Belt (Ill., Mo., Ind., and Ohio) was considered as a group.
3. Additional soil samples, representative of the variability encountered in the agricultural soils of the lower Corn Belt, should be analyzed to verify these results.

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