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Measuring Soil Carbon with Intensive Soil Sampling and Proximal Profile Sensing

Eric Lund, Veris Technologies, Inc. Salina KS

Chase Maxton, Veris Technologies, Inc. Salina KS

Tyler Lund, Veris Technologies, Inc. Salina KS

Abstract

Soils have a large carbon storage capacity and sequestering additional carbon in agricultural fields can reduce CO2 levels in the atmosphere, helping to mitigate climate change. Efforts are underway to incentivize agricultural producers to increase soil organic carbon (SOC) stocks in their fields using various conservation practices. These practices and the increased SOC provide important additional benefits including improved soil health, water quality and – in some cases – biodiversity. Many current initiatives offer only a relatively modest payment per acre with little or no field validation of actual SOC sequestered. This is due to the concern that measuring actual SOC change accurately in farm fields is impractical and uneconomical. However, if agricultural producers are to receive adequate compensation for their carbon sequestering efforts, baseline soil carbon inventories and follow-up measurement and verification are needed. In late 2021 an intensive soil measurement project was conducted on four 16 ha fields in the US Midwest. This project included collecting lab-analyzed soil samples to depths of 90 cm and 30 cm on .4 ha and .1 ha grids respectively, and soil sensor profiling technology that included NIR, EC, and compaction sensing. In all, 184 0-90 cm sensor probe investigations were completed and over 1200 lab samples were analyzed. The objectives of the project were to: 1) Create a high quality, lab-analyzed SOC baseline that could be used to evaluate SOC measurement and modeling approaches, 2) Evaluate the extensive lab sample dataset to improve understanding of lab estimations of field SOC, bulk density, and soil profile SOC, and 3) Evaluate the performance of sensor probe technology including using sensors to estimate SOC at unsampled locations. Results of the project reveal important considerations for measuring bulk density, lab-analyzed sample repeatability, and soil sensor calibration methods.

Keywords.
Soil carbon, proximal sensing, Vis-NIR, EC, bulk density, measurement, verification

Introduction

Since 1850, soils have lost an estimated 78 gigatons (GT) of carbon, primarily due to cultivation (Lal, 2009). This loss of soil carbon represents a significant portion of greenhouse gas emissions and has resulted in the degradation of agricultural soil quality worldwide. Using practices that restore carbon, such as no-till farming and planting cover crops during fallow periods, carbon can be sequestered in the soil. Carbon sequestration has the potential to offset fossil fuel emissions by 0.4 to 1.2 GT of carbon per year, or 5 to 15% of the global fossil-fuel emissions (Lal, 2004). Farmers and landowners would be adequately paid for adopting carbon-sequestration techniques, provided their increases in carbon can be measured, reported, and verified. Currently, most programs offer small payments for merely adopting practices, with few if any soil carbon measurements. Growers are accustomed to being compensated for the value of what they produce and have been reluctant to enroll in programs that do not compensate them for the tons of carbon their fields sequester (Gullickson, 2021).

Accounting for soil carbon changes is difficult, because carbon increases due to farming practice changes are very small, and carbon varies widely within a field, even within a few meters, and within the soil profile. In addition to the variances in carbon %, the soil bulk density must also be accounted for, especially since adopting conservation practices will likely change the bulk density. To verify that carbon has been sequestered, a baseline must be established at the beginning of the project, along with subsequent measuring to verify the carbon change. The amount of carbon that is accredited will be based on the confidence, likely at the 90% level of those measurements (Willey and Chameides, 2007). The confidence interval is determined by the number of samples and the variability of the carbon. If the standard deviation is large, additional samples are required to reduce the confidence interval. If the sampling rate is insufficient, the carbon payment discount due to the uncertainty will be large. If an adequate number of samples are collected, the cost of conventional soil sampling and lab analysis could be excessive. An alternative that generates large numbers of carbon measurements at a very low cost per sample must be considered. In addition to lab analyses, rapid carbon assessment methods being proposed include near-infrared reflectance (NIR), remote imagery, carbon cycle modeling, passive gamma sensing, laser-induced breakdown spectroscopy, and more. To ultimately evaluate and compare the performance of different methods, a baseline carbon inventory using extensive sampling and lab analysis was conducted on a set of fields in Iowa, Nebraska, and Kansas. The first approach that was evaluated on these fields was a proximal sensing technology that uses a suite of sensors including visible and NIR optical measurements. Soil NIR has been shown to correlate well with soil carbon (Sudduth and Hummel, 1993; Reeves et al.,1999; Shepherd and Walsh, 2002).

Materials and Methods

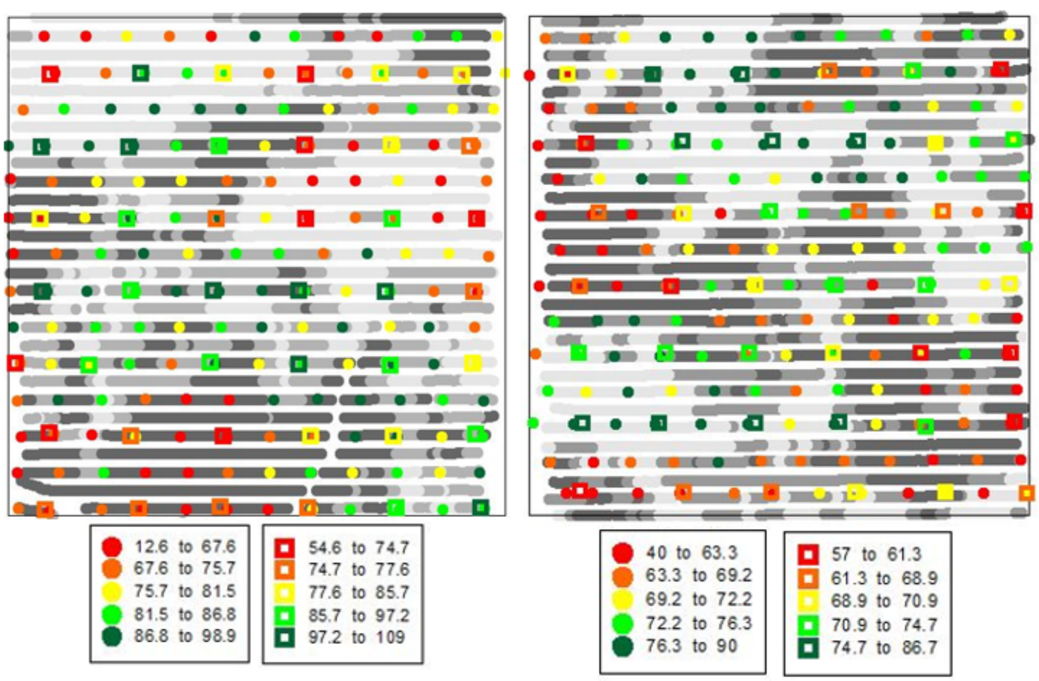
Soil Sampling and Lab Analyses

Four fields were selected that represent typical Midwest fields, with varying levels of soil variability. The Iowa field contained seven different USDA-SSURGO soil types, while the Nebraska field had one USDA-SSURGO soil type (Table 1).

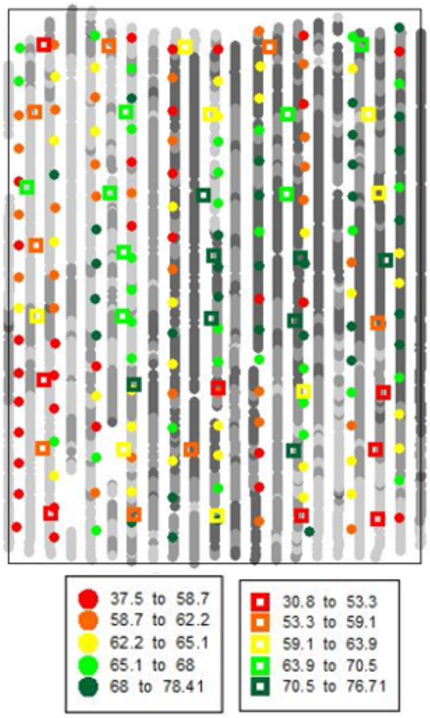
Table 1. Field locations, soil types, and data collected

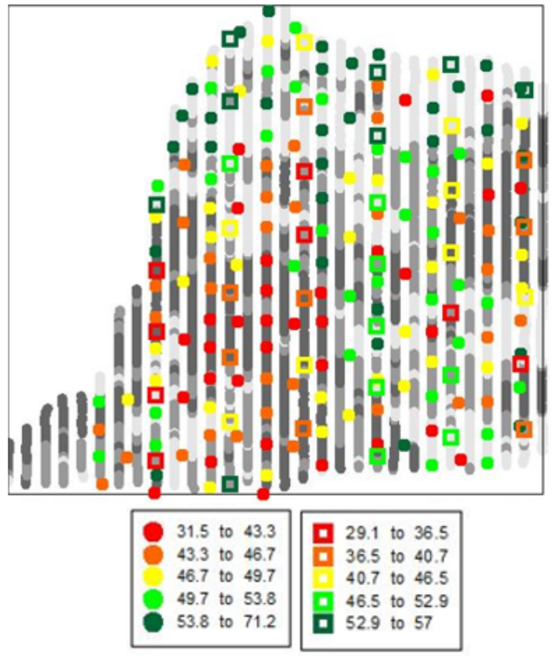
State	County	SSURGO soil types	Field Size-ha	No. of 0-90 cm cores on .4 ha grid	No. of 0-30 cm cores on .1 ha grid	No. of 0-90 cm Sensor Probe insertions
Iowa	Mahaska	Wiota silt loam, Nevin silty clay loam, Bremer silty clay loam, Radford silt loam, Ely silty clay loam, Otley silty clay loam, Judson silty clay loam	17	42	168	47
Nebraska	York	Hastings silt loam	17	42	168	47
Kansas1	Saline	Cozad silt loam, Hord silt loam, Detroit silty clay loam, Sutphen silty clay loam	16	40	160	45
Kansas2	Saline	Longford silt loam, Crete silt loam	16	40	160	45

Data collection on all fields was done in the fall of 2021 following harvest prior to any tillage activity. On each field, samples were collected on .4 ha (1 ac) and .10 ha (.25 ac) grids (Figures 1-4). The .4 ha grid samples were 0-90 cm (35.4 in) deep and sample tube dimensions as follows: cutting shoe diameter 3.5 cm (1.375 in.), liner inner diameter 4.1 cm (1.625 in.). the .10 ha grid samples were collected to a depth of 30 cm (11.8 in.) with sample tube dimensions as follows: cutting shoe diameter 4.76 cm (1.875 in), sample tube inner diameter 5.4 cm (2.125 in). Samples were segmented into 30 cm lengths (11.8 in) and analyzed by Ward Laboratories, Kearney NE using dry combustion methods for carbon percentage and bulk density using undisturbed soil methodology. Coarse gravel fragments were not evident in any of the soil samples.



Figures 1-2. (Left to right) Iowa and Nebraska fields showing U3 transects (monochrome), 0-30 cm MgC/ha lab analyzed values for .10 ha grids (circles) and .4 ha grids (squares)





Figures 3-4. (Left to right) Kansas 1 and Kansas 2 fields showing U3 transects (monochrome), 0-30 cm MgC/ha lab analyzed values for .10 ha grids (circles) and .4 ha grids (squares)

Proximal Sensor Mapping and Profiling

Each field was mapped with a Veris® U3 Soil Mapping System which measures soil electrical conductivity (EC), and soil optical reflectance using red and infrared wavelengths (Figure 5). EC measurements have been shown to be correlated with soil texture (Kitchen et al., 1998), and optical reflectance with soil organic matter (Kweon, 2012). Fields were mapped on 15.2 m (50 ft) transects. These maps were used to provide an overall view of the soil variability and to aid in selecting calibration points for the Veris® P4000 sensor probe (Kweon, et al., 2009). The P4000 probe containing EC, optical, and insertion force sensors was used to collect soil profile measurements to a depth of 90 cm (Figure 6). At each of the .4 ha grid sample locations on each field the sensor probe was inserted hydraulically adjacent to each of the 0-90 cm core samples. At five additional locations in each field, a set of 0-90 cm lab-analyzed soil cores and adjacent 0-90 cm sensor probe insertions were conducted to calibrate the sensor readings to the adjacent cores (Figure 7).



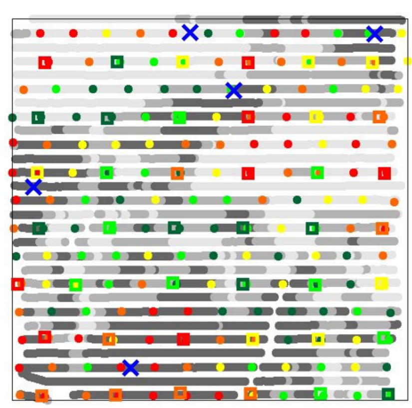


Figure 5 and 6. Veris U3 (left) and P4000 (center). Figure 7. Example map showing blue X's that mark sensor probe calibration location. Squares mark .4 ha grid samples, sensor probe insertions, and location of sensor probe estimates of SOC.

To evaluate the accuracy of the carbon estimates from the sensor probe, a regression model from five calibration sites on each field was created and evaluated, using 30 cm soil segments matched with 30 cm of sensor probe data (Figure 8). The model was subsequently applied to the profile sensor data from the .4 sites to estimate the carbon, and those estimated were compared to the actual from the adjacent lab-analyzed soil cores.

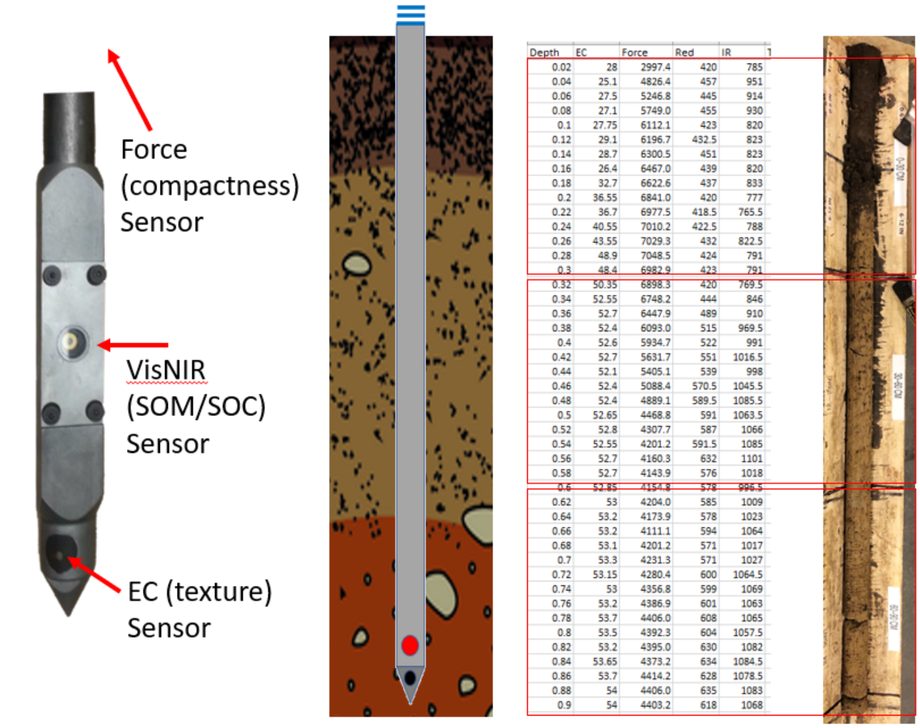


Figure 8. P4000 sensors, segmented probe insertion data with segmented calibration core.

Results

Soil Sampling and Lab Analyses

Lab-analyzed soil carbon %, bulk density, and MgC/ha from the 0-90 cm core samples collected on a .4 ha grid reveal that each field had a wide range of carbon within the field and within the profile. Bulk density was less variable (Table 2).

Table 2. Soil Properties (at .4 ha grid points)

		Range			Field Average			Co-efficient of Variation		
State	Depth-cm	Carbon %	Bulk Density	MgC/ha	Carbon %	Bulk Density	MgC/ha	Carbon %	Bulk Density	MgC/ha
Iowa	0-30	1.1-2.4	1.3-1.7	51-109	1.81	1.52	82.6	0.18	0.05	0.17
Iowa	31-60	.4-2.2	1.3-1.7	20-101	1.3	1.52	58.6	0.38	0.06	0.36
Iowa	61-90	.2-2.1	1.4-1.7	12-95	0.78	1.58	36.5	0.56	0.05	0.53
Nebraska	0-30	1.3-2.1	1.3-1.5	57-87	1.61	1.44	69.3	0.12	0.05	0.1
Nebraska	31-60	.3-1.9	1.2-1.6	15-74	0.9	1.43	38.1	0.35	0.07	0.29
Nebraska	61-90	.2-1.2	1.0-1.6	9-48	0.49	1.4	20.9	0.43	0.08	0.44
Kansas1	0-30	.7-1.7	1.4-1.6	31-75	1.31	1.46	57.7	0.19	0.06	0.21
Kansas1	31-60	.7-1.5	1.3-1.6	30-63	1.08	1.44	46.8	0.19	0.05	0.19
Kansas1	61-90	.6-1.4	1.3-1.6	26-67	0.93	1.5	41.7	0.26	0.05	0.26
Kansas2	0-30	.7-1.3	1.3-1.5	29-57	1.02	1.43	43.5	0.2	0.04	0.19
Kansas2	31-60	.4-1.2	1.3-1.6	20-55	0.75	1.46	32.9	0.27	0.05	0.27
Kansas2	61-90	.2-1.8	1.3-1.7	9-73	0.65	1.51	28.9	0.46	0.05	0.4

The intense soil sampling on each field provided an opportunity to compare the field carbon measured from two detailed sets of samples on all four fields. The lab-measured carbon from the .10 ha 0-30 cm samples was compared to nearby 0-30 cm segments from the .4 ha grid 0-90 cm cores. Only cores that were within 10 m of the .40 ha grids were used. The results show a difference for carbon at the 0-30 cm on each field that ranged from just over 1 Mg C/ha to nearly 7 Mg C/ha (Table 3). The differences in sample tube diameters could be part of the cause, however there was no systematic bias between the two probe sizes. Also, the % C showed similar differences and % C is independent of sample tube sizes.

Table 3. Variance in estimates of 0-30 cm field carbon

State	% C from .1 ha samples	% C from .4 ha samples	Field Mg C/ha estimated from .1 ha samples	Field Mg C/ha estimated from .4 ha samples	Mg C/ha Difference
Iowa	1.78	1.84	77.0	84.0	7.0
Nebraska	1.57	1.60	70.5	69.3	1.2
Kansas1	1.50	1.31	62.7	57.7	5.0
Kansas2	1.13	1.02	48.3	43.5	4.8

Proximal Sensor Mapping and Profiling

At five locations within each field, the 0-90 cm readings of visible and NIR reflectance, soil EC, and insertion force from the sensor probe was calibrated to adjacent 0-90 cm lab-analyzed core samples. The sensor datasets were divided in 0-30, 31-60, and 61-90 cm segments and values averaged for each segment and then matched with the corresponding core segments. The results of the bivariate regression between NIR and fifteen 30 cm soil carbon segments were significantly correlated (Figure 9).

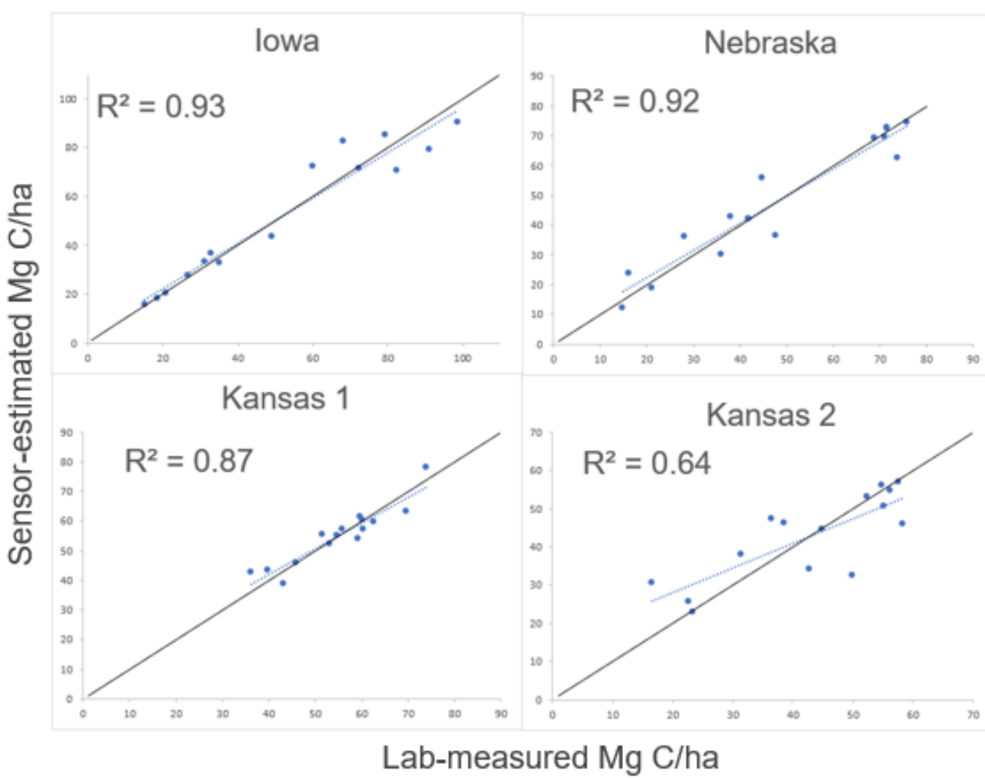


Figure 9. Correlation of sensor probe data with lab-measured C at calibration sites

The regression model from the five calibration sites was subsequently applied to the profile sensor data from the .4 sites to estimate the carbon, and those estimates were compared to the actual from the adjacent lab-analyzed soil cores. Estimated C at those .4 ha grid points using only sensor probe data were well correlated with the actual C measured (Figure 10).

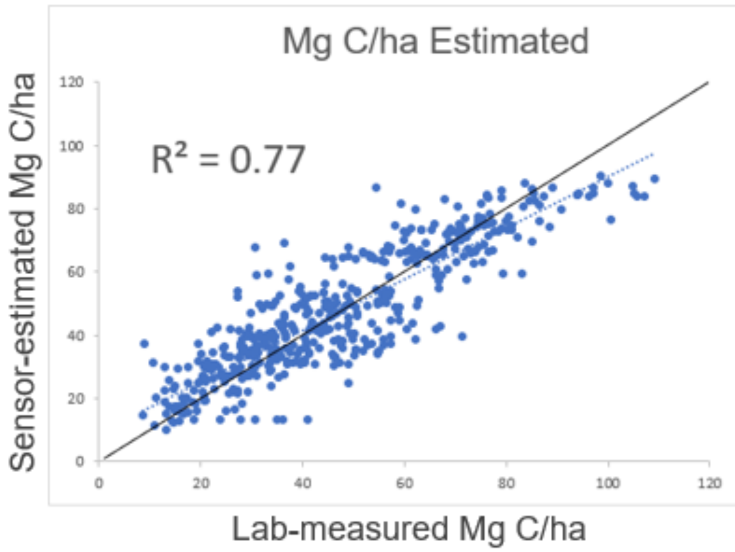


Figure 10. Correlation between carbon measured and estimated at .4 ha grid points on all four fields using sensor probe regression model from five 0-90 cm samples/field.

An important component of optimizing the sensor probe's calibration is to capture a range of carbon in the calibration set that represents the field's full carbon variability. Two methods of selecting calibration sites for the sensor probe were evaluated: 1) Using visual cues from the U3 transect map and topography to identify areas of suspected significant variations, and 2) Stratifying the reflectance values from the sensor probe to choose calibration sites. The second method proved to result in closer estimates of the carbon measured in the lab samples (Table 4).

Table 4. Two sets of lab-measured C and two sensor probe estimation approaches (0-30 cm)

State	Field Mg C/ha measured by .1 ha samples	Field Mg C/ha measured by .4 ha samples	Field Mg C/ha estimated by sensor probe (unstratifed sites)	Field Mg C/ha estimated by sensor probe (stratified sites)
Iowa	77.0	84.0	71.1	82.2
Nebraska	70.5	69.3	66.2	71.3
Kansas1	62.7	57.7	59.8	65.1
Kansas2	48.3	43.5	53.1	45.2

Discussion and Summary

The intensive soil sampling and lab analyses, coupled with equally intensive proximal sensor investigations, produced several findings that will likely impact future efforts to measure and verify soil carbon levels:

- As other studies of soil carbon have found, there can be a wide range of soil carbon levels within a field (McBratney and Pringle, 1997; Kweon, 2012). This study confirmed those variations and showed significant soil carbon variability exists within the soil profile as well. On every field, at least one core location had comparable or greater carbon at 60-90 cm than another location within the same field had in the 0-30 cm depth.

- 55% of the soil carbon was discovered deeper than 30 cm. Some of the current carbon measurement initiatives are limited to that depth due to the challenge of collecting cores deeper than 30 cm. Other modeling approaches are attempting to model the deeper depths based on measurements from the shallower depths. However, the 31-90 cm carbon was only weakly related to the 0-30 cm carbon (Figure 11).

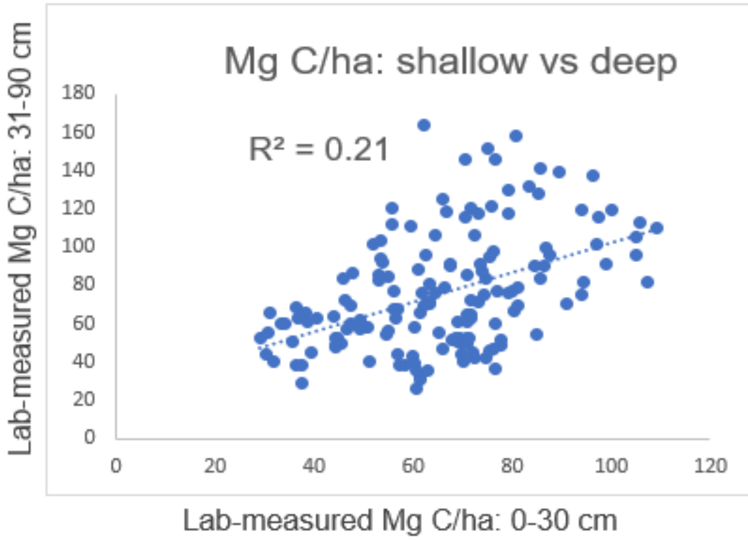


Figure 11. 0-30 cm carbon correlated with 31-90 cm carbon

- The variation in bulk density was low, compared to the carbon variations. All sampling was completed in the fall following harvest, prior to any tillage operation and winter freeze-thaw effects, which may have contributed to bulk density consistency within fields, within the profile, and even between fields and profiles.
- Two intensely sampled lab C inventories produced different results, with differences ranging from 1.2 to 7.0 Mg C/ha. Across all four fields, the carbon from one 0-30 cm inventory to another varied by an average of 7%. This difference has implications for measuring sequestered soil carbon, which may only increase by 10% over several years.
- The difference between lab-analyzed carbon inventories also has implications for comparing alternative methods of estimating carbon, including proximal sensors. The carbon estimated by sensor probes showed a smaller variance between the average of the two lab-analyzed inventories, than the two inventories from each other.
- The sensor probe measurements were well-correlated with lab measurements. To accurately predict carbon at locations that are not part of the calibration, it was found that selecting calibration locations that represent field variations is crucial.
- Sensors can quickly collect a large number of measurements which provides an affordable opportunity to reduce the confidence interval and subsequent uncertainty discount. The cost for collecting and analyzing a 0-90 cm core sample vs. a 0-90 cm sensor probe insertion is likely a factor of 5-10X.
- Next steps: Future projects need to investigate and attempt to reduce the differences between lab-analyzed carbon inventories, and at the same time identify possible differences between testing labs, which was not part of this project. The relative consistency of bulk density needs to be confirmed, especially when collecting data in the spring or whenever bulk density variations may be more pronounced. The use of proximal sensors was found to be promising and needs ongoing inclusion in soil carbon research. Continual advancements in sensors and in stratification/calibration methodologies likely improve their effectiveness.

Acknowledgements

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