Using Soil Samples and Soil Sensors to Improve Soil Nutrient Estimations

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Abstract

Estimating soil nutrient levels, especially immobile nutrients like P and K, has been a primary activity for providers of precision agriculture services. Soil nutrients often vary widely within fields and growers have been eager to manage them site-specifically. There are many causes of the variability, including pedogenic factors such as soil texture, organic matter, landscape position, erosion, and other natural factors that have resulted in an accumulation of unused nutrients in some areas of the field, while in other areas of the field nutrient levels are low. There are also anthropogenic, man-caused nutrient variations. Lab-analyzed soil sampling is a key component of soil nutrient management, however only a tiny fraction of the soil within a field can be sampled and measured. Zone sampling is a method that acknowledges the pedogenic nature of the variability and attempts to identify zones where nutrients vary based on productivity and natural soil causes. Alternatively, the approach that accounts for the bulk of USA precision sampling is based on a standardized sampling pattern, typically a 1 ha systematic grid. Grid sampling does not consider the pedogenic factors between sample points and uses various interpolation methods to provide estimates between the sample points. The spatial variations of soil nutrients within 1 ha have been widely reported. The errors caused by not identifying these variations and simply interpolating the point data can be significant, sometimes greater than the errors from a single rate. One method of reducing these errors is co-kriging. This geostatistical approach uses a densely sampled dataset, typically from a proximal sensor, along with the grid sampled nutrient tests to estimate nutrient levels between the grid points. One of the key limitations of co-kriging is the large number of samples at various spatial distances needed to create the appropriate geostatistical model for each field. As a result, co-kriging has not been commercially available for precision agriculture and has been limited to research endeavors. Recently, Veris Technologies has tested an approach similar to co-kriging but with several important differences. One, instead of one soil sensor data layer as has been the case with most co-kriging studies, the new approach investigates multiple soil attributes to a soil profile depth of 60 centimeters. This improves the opportunity for determining the pedogenic variables that drive nutrient variations. Two, these sensor layers provide important information about the nature of overall spatial variability in the field, providing the rationale for interpolation options. Three, in addition to filling in the space between sample points with grid interpolation or sensor-derived data, the new approach allows the use of nutrient field average values when appropriate to minimize large errors. Four, machine-learning techniques are applied to optimize the estimations. The novel approach has been tested on several USA fields and compared to conventional soil sampling.

Keywords.
nutrients, fertilizer, phosphorous, potassium, pH, soil, variable, grid, sampling, pedogenic, interpolation, machine learning

Introduction

Estimates of nutrient levels in US farm fields is typically accomplished from lab-analyzed soil samples. Modern methods using GPS are primarily done using a 1 ha grid with 5-10 soil cores collected in a 3-6 m radius, resulting in a lab-analyzed sample every 100 m. Many US soil testing laboratories participate in accreditation services, such as the North American Proficiency Testing (NAPT). As a result, these labs provide highly accurate and repeatable soil measurements *at the sample sites*. However, 95% of the field's soil is not sampled. Various methods of interpolating the results of the grid samples are employed to estimate the values of the unsampled areas. Research has found that these estimates, while accurate at the sample locations, can be highly inaccurate between sample sites due to the unpredictable nature of the soil nutrient variability (Bianchini and Mallarino, 2005; Brouder et al., 2005). In some cases, using a field average uniform rate had lower errors than 1 ha grid samples, when accuracy of grid estimations were validated using independent samples (Lund et al., 2004). Sensors have been developed that proximally sense soil properties such as pH, organic matter, and clay content, but no soil sensor for immobile nutrients such as soil test phosphorous (P) have been proven effective. Nutrients such as P are tightly bound to the soil colloid and require chemical extraction.

Although grid-sampling is desirable from a service-provider standpoint due to its simplicity, it ignores the underlying soil properties that can cause nutrient variations. Understanding basic agronomic principles of how crops use nutrients has led to generalized observations about nutrient variability. With the advent of yield monitoring in the late 1990's, growers found that the poorer yielding areas of their fields frequently had higher nutrient levels than better producing areas, likely because under a uniform application of fertilizer the poorer producing areas stored unused nutrients, while more productive areas depleted their nutrient availability. Nutrient variability has also been found to vary with soil erosion and deposition, differences in parent material, and other pedogenic phenomena (Franzen, 2018). Management zone sampling methodologies were proposed to help capture these nutrient variations (Fraisse et al., 2001, Jaynes et al., 2005, Franzen, 2018) Proximal sensing of soil properties such as clay, because of its large role in water-holding capacity and productivity, was used to improve nutrient sampling efforts (Kitchen et al., 2005). The relationship between any single soil property and nutrients is not consistent, however. Relationships can be positive, inverse, and insignificant (Huang et al., 2018; Maxton and Lund, 2020).

Grid sampling is growing in popularity and the majority is a 1 ha grid cell size. Based on the body of nutrient variability research showing wide variations within 1 ha, one can conclude that many fertilizer scripts over and under apply nutrients within the grid cells. This leads to the question: what can be done to improve grid sampling estimations? Wide and sudden nutrient variations between sample points make it impossible for interpolations alone to estimate accurately. Pedogenic soil properties may be able to help, but soil properties don't always relate to nutrients. There can be anthropogenic factors such as misapplications, old livestock pens, merged fields, etc. that are the major cause of nutrient variations in some fields.

Recently, Veris Technologies tested a nutrient management approach using a sensor probe that measures multiple pedogenic soil properties in the top 60 cm, including sensors for soil OM, soil texture, soil moisture, and compaction. These soil properties relate to productivity and can have a relationship to how soil uses, loses, and stores crop nutrients. The objective was to determine if grid sampling can be improved by mapping multiple pedogenic factors and applying machine learning techniques to better understand soil-nutrient relationships, with a goal of improving estimations between lab sample locations.

Materials and Methods

Sensing Technology and Calibration

The Veris CoreScan™ is a hydraulically-activated probe that utilizes four different sensors to characterize the soil profile in 1 cm increments to a depth of 60 cm in automatic mode. In manual mode the CoreScan can collect 0-90 cm measurements. The sensors on the CoreScan probe are as follows: Soil EC from a dipole array cone tip, soil reflectance from 660nm and 950nm wavelengths of the visible and near infrared (Vis-NIR) spectrum, capacitance/dielectric sensor, and a load-cell based penetrometer (Figures 1 and 2). These sensors relate to soil texture, soil organic matter (SOM), soil moisture, and compaction, respectively. In combination and with lab-analyzed soil samples, they can be used to model: bulk density, horizon depth, profile water-holding capacity, depth to limiting layer, and more.

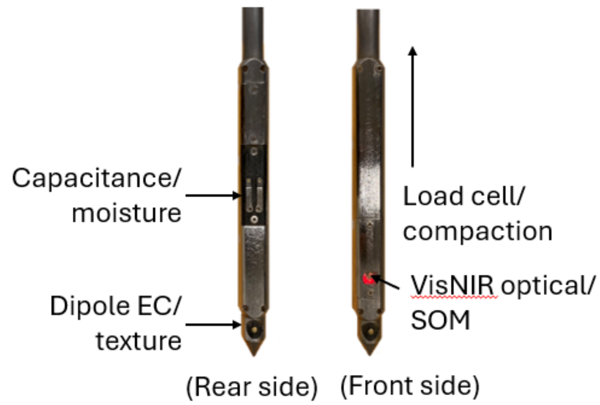

Figure 1. Veris CoreScan platform--UTV mounting *Figure 2.* CoreScan sensing technologies

The CoreScan is automated to deliver high through-put. Each insertion is controlled and monitored from a V-Sense controller and tablet PC running CoreScan data acquisition software. To prevent probe damage, the system is designed to stop inserting when insertion force reaches a user-selectable threshold, typically 7.5 MPa for a UTV mounting and 12 MPa for a tractor mounted system. In “continuous” mode the CoreScan senses when the vehicle has stopped and automatically inserts the probe, with no action from the operator. Each cycle takes approximately 50 seconds including travel time between insertions, which provides a capacity of ~25-30 ha/hour on a .4 ha spacing. Profile logs from each sensor can be viewed during data collection and post data collection (Figures 3a-d).

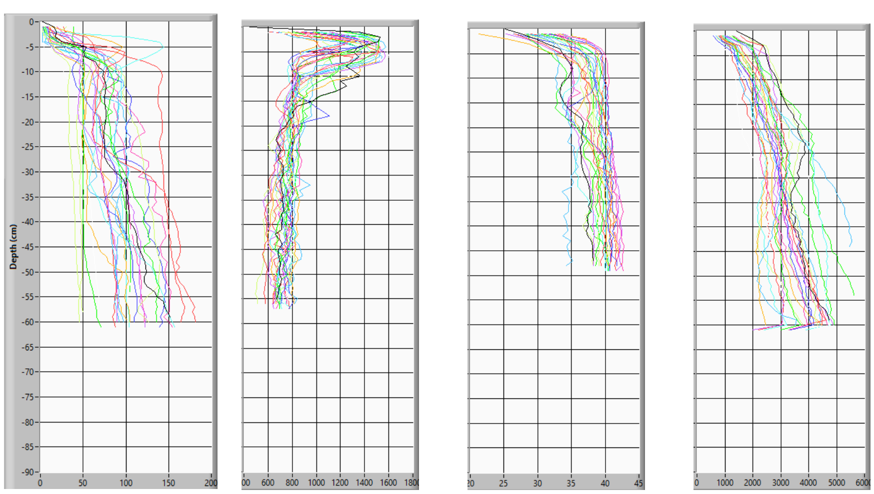

Figure 3a-d: a. soil EC b. Infrared reflectance c. soil moisture d. insertion force

Field data collection

In the fall of 2023 and spring of 2024, sensor probing and nutrient sampling was conducted on 10 fields in five US cornbelt states. 3 fields were in the central cornbelt (CCB), 2 in the eastern cornbelt (ECB), 3 in the northern cornbelt (NCB) and 2 from the western cornbelt (WCB). All fields were sensor-probed (CoreScan) to a depth of 60 cm on a .4 ha grid. A minimum of six 0-15 cm calibration samples were collected from each field, typically on a 1 ha grid with an average of 10 samples per field. Samples were lab-analyzed for available and available plus reserve phosphorus (P1 and P2), potassium (K), and soil pH, along with organic matter (OM) and cation-exchange capacity (CEC). One field included additional validation samples for use in validating various sampling and sensing approaches.

Results and Discussion

Lab-analyzed soil properties

The lab measurements showed that across all fields the soil nutrients ranged widely, although variations within some of the fields were low (Table 1).

Table 1. Descriptive statistics for lab-measured soil pH, phosphorous, and potassium

		pH (units)				P1 (ppm)				P2 (ppm)				K (ppm)			
Field	*N*	*Min*	*Max*	*SD*	*Avg*	*Min*	*Max*	*SD*	*Avg*	*Min*	*Max*	*SD*	*Avg*	*Min*	*Max*	*SD*	*Avg*
CCB1	10	5.7	7	0.43	6.3	3	10	2.5	5.7	5	17	3.6	8.3	87	121	13.5	101.2
CCB2	13	5.6	7	0.40	6.2	17	76	18.4	51.7	22	95	22.9	66.4	173	404	62.4	292.6
CCB3	7	5.5	7.5	0.82	6.4	5	49	15.6	22.3	7	64	19.8	31.7	54	140	33.5	93.3
ECB1	17	5.2	6.6	0.30	6.0	59	122	22.1	89.1	66	139	22.6	106.7	173	492	104.2	274.4
ECB2	6	5.9	6.8	0.36	6.4	11	49	13.5	24.5	24	61	15.8	41.5	84	172	36.7	130.2
NCB1	7	6.6	7.3	0.29	6.9	48	58	4.0	53.4	68	94	10.7	77.8	148	229	32.4	202.6
NCB2	7	6.3	7.1	0.28	6.8	33	42	3.9	36.0	40	56	5.6	48.1	250	359	33.6	311.7
NCB3	8	6.5	7.6	0.34	7.1	50	169	38.7	83.9	56	170	35.1	96.5	242	651	135.8	386.8
WCB1	12	5.9	7.1	0.44	6.6	26	119	29.8	74.9	67	157	28.5	120.1	319	842	173.3	514.1
WCB2	15	4.2	5.2	0.33	4.9	16	134	42.3	50.1	22	136	45.0	59.7	198	543	125.5	319.3

Sensor measurements and relationship to nutrients

Whether it’s appropriate to use pedogenic soil properties in a nutrient script is largely dependent on the strength of the relationship between the measured nutrients and available pedogenic soil attributes. That relationship in turn is largely dependent on soil formation and historical productivity differences in the field that has led to nutrients being mined, banked, or lost according to variations in the soil attributes. The correlation between the CoreScan’s suite of soil sensors and two primary nutrients and pH was evaluated, and the best correlation identified (Table 2). Color coding shows both the strength of the relationship and whether it was inversely or positively correlated. The relationships to P and K were more variable, with darker/higher OM and higher EC/clay content soils having both positive and inverse relationships. Soil pH was more consistently positively correlated with EC and inversely to optical reflectance. That follows an expected pattern—soils with more clay and OM are more highly buffered to resist acidification.

Table 2. Pearson's Correlation Table for lab-measured properties and sensor used

Table 2 legend		P1	Sensor	P2	Sensor	K	Sensor	pH	Sensor
.75|1	CCB1	-0.42	EC_15	-0.45	Red_15	-0.53	Moist_30	-0.85	IR_60
.50|.75	CCB2	-0.75	Red_60	-0.71	Red_60	-0.88	Red_60	-0.50	IR_60
.25|.50	CCB3	0.68	Red_45	0.70	Force_60	0.67	Red_45	-0.86	Red_15
0.0|.25	ECB1	-0.54	EC_60	-0.52	Red_60	-0.80	Red_60	0.72	EC_15
0.0 |-.25	ECB2	-0.97	EC_45	-0.76	EC_45	-0.65	IR_30	0.98	EC_60
-.25|-.50	NCB1	-0.88	IR_30	-0.95	IR_30	0.85	Moist_30	0.99	EC_15
-.50|-.75	NCB2	-0.77	IR 0-60	0.79	EC_60	-0.91	IR 0-60	0.77	Moist_30
-.75|-1	NCB3	-0.37	Moist_30	-0.39	Moist_30	-0.56	Force_30	0.92	EC_30
	WCB1	-0.43	Moist_15	0.51	Red_45	-0.38	IR_15	0.46	Red_45
	WCB2	-0.76	IR 0-60	-0.79	IR 0-60	-0.70	IR 0-60	0.81	EC 15-30

The minimal acceptable correlation to be included in further analyses and possible nutrient estimations was arbitrarily set at .50 *r* threshold. For each nutrient and field that met this threshold the average prediction errors for each lab-measured soil chemical property based on the Root Mean Square Error (RMSE) of the calibration and the quality of the calibration expressed as Ratio of Performance to Deviation (RPD: standard deviation/RMSE) are shown in Table 3 and cross-validated results in Table 4.

Table 3. Avg. calibration results

	R^2	RMSE	SD	RPD
P1 (ppm)	0.59	10.9	17.1	1.57
P2 (ppm)	0.52	14.5	21.4	1.47
K (ppm)	0.54	41.4	64.2	1.55
pH (units)	0.65	0.19	0.39	2.05

Table 4. Avg. leave-one-out cross validation results

	R^2	RMSE	SD	RPD
P1 (ppm)	0.40	13.2	17.1	1.30
P2 (ppm)	0.32	17.3	21.4	1.24
K (ppm)	0.3	50.9	64.2	1.26
pH (units)	0.54	0.25	0.39	1.56

One of the objectives of this study was to determine whether using several sensors mapping multiple pedogenic soil attributes could explain nutrient variability better than a single sensor and fewer soil attributes. The single sensor chosen was soil EC as EC maps are widely available and have been shown to relate well with soil texture, water and nutrient-holding capacity, and in turn productivity (Kitchen et al., 2003). Data used in the analysis as the single variable was the 0-60 cm depth from the CoreScan. The multiple sensor dataset included EC, Vis-NIR optical, moisture, insertion force, each at the 0-15, 15-30, 30-60, and 0-60 cm depths. Each sensor and each soil nutrient attribute was evaluated individually with bivariate regression. Results of the analysis show that measuring multiple potential soil attribute drivers triples the likelihood of discovering a mapped soil attribute that meets the nutrient correlation threshold (Table 5).

Table 5. No. of fields >.5 r

	Mult. Sensors	% of fields	Single Sensor (EC 0-60 cm)	% of fields
P1	7	70%	2	20%
P2	8	80%	1	10%
K	8	80%	3	30%
pH	9	90%	4	40%

Machine Learning

The results shown in Tables 3-5 show promising results of improving understanding of nutrient variability by measuring multiple pedogenic-based soil properties throughout the 0-60 cm profile. However, considering the sensor measurements one at a time using simple regression is unlikely to be the optimal way to deal with the complexities of soil nutrient and pedogenic soil variations. In an initial Machine Learning exercise on this dataset, 100 samples were used for a training dataset in a Gradient Boosted Trees machine learning model (Figure 4a). Fifty samples were used for validation (Figure 4b). While this exercise demonstrated increased R^2 and comparable RPD's due in part to an increased range of each soil property, it resulted in higher RMSE's (Table 6). By reducing the sampling and lab-analysis cost by 1/3, a lower level of accuracy might be acceptable in some situations. The fields in this project were typically 100-200 km apart, all farmed by different operators and different fertilizing and production practices. Machine learning approaches also need to be evaluated in a real-world setting, such as a single 1000 ha farm operation where soil types and historical fertilization practices have likely been more similar.

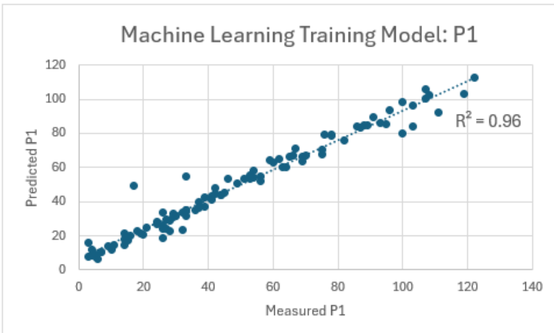

Figure 4a. ML training model for P1.

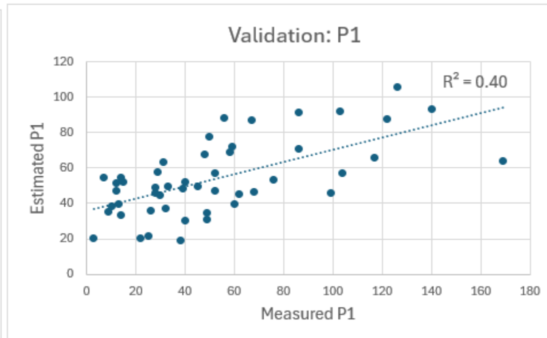

Figure 4b. Validation scatter plot for ML-predicted P1.

Table 6. Machine Learning Validation Results

	R^2	*RMSE*	*SD*	*RPD*
P1	0.40	29.6	38.4	1.29
P2	0.48	29.7	40.6	1.37
K	0.48	113.5	148.6	1.31
pH	0.65	0.45	0.75	1.67

Fertilizing scripts using Pedogenic-Enhanced Grid Sampling

The effectiveness of a pedogenic-based grid sampling approach depends on accomplishing these steps:

1. Overall methodology must be science-based, transparent, reproduceable, and validated.
2. Accurate lab-analyzed soil samples are the nutrient foundation—collecting 8-12 geo-referenced cores per sample, analyzed in an accredited laboratory.
3. Accurately measured, multiple pedogenic soil properties: there are many causes of nutrient variability and measuring more possible causes improves likelihood of discovering the proper relationships.
4. Relationships between soil nutrients and pedogenic soil properties discovered, understood, and advanced, likely using machine learning.
5. At each spot within a field, for example each 10 m x 10 m cell, there is a choice of using: the interpolated estimate from a grid sample, a pedogenic soil-based calibration estimate, field average value, or a combination. A 1 ha grid cell graphic depicts these choices and the "dials" that can be used to adjust estimates (Figure 5).

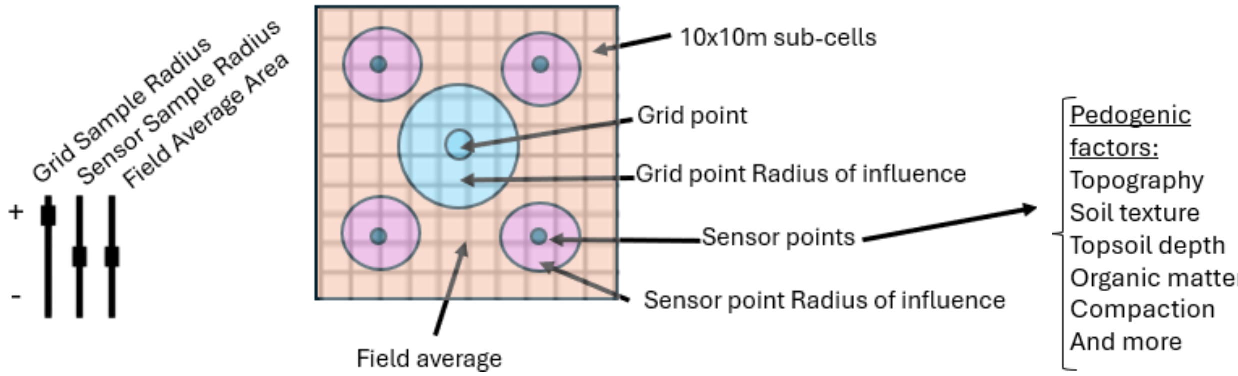

Figure 5. 1 ha grid cell example of Pedogenic Enhanced Grid Sampling, showing options for estimating nutrient estimations at each 10m x 10m sub-cell.

A variety of decision rules can be envisioned. Some are intuitive, such as closer proximity to the grid sample location favors using the interpolated estimate. Similarly, the stronger the correlation between a soil nutrient and a pedogenic soil property, the more likely to include the estimate from the nutrient-pedogenic relationship. Minimizing estimation errors are a main goal, so wide variances of adjacent grid samples suggest caution in interpolating, as would major changes in pedogenic soil and topo attributes between grid samples. In situations where there is not an adequate soil-based estimate, and grid point interpolation shows risk, the field average level of the nutrient would likely be the safe alternative. Additional datasets including topography and crop imagery and innovative machine learning approaches are needed to optimize the decision-making script-creation.

A basic version of the Pedogenic Enhanced Grid Sampling methodology was performed on Field WCB2. This 24 ha field was grid-sampled on 1.6 ha and sensor-probed on .4 ha. The best correlation between CoreScan sensors and P1 was the IR 0-60 cm data with a .58 R^2. 25 validation samples were collected. A calibration between the sensor probe and each nutrient was developed (Figure 6).

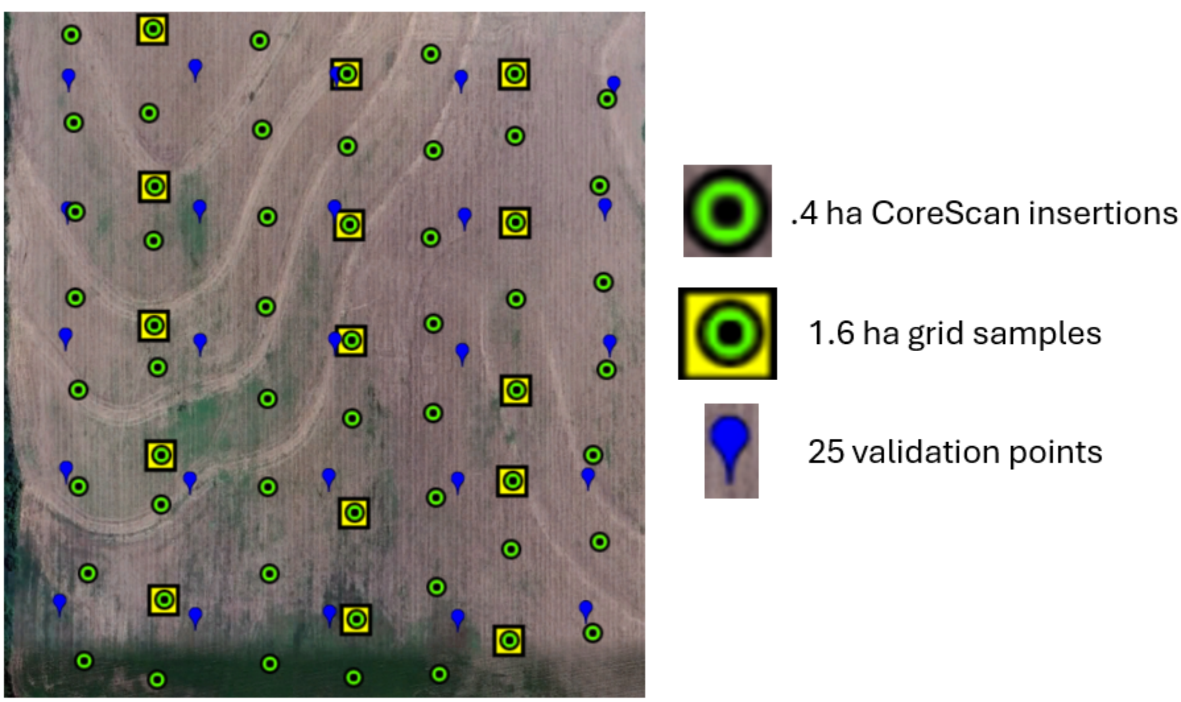

Figure 6. WCB2 field with locations of: 1.6 ha grid samples, .4 ha sensors probe insertions, and 25 validation sites.

A combination of sensor-estimated P1 and lab-measured P1 was created as follows: the P1 and IR 0-60 cm calibration estimated P1 was applied at the .4 ha CoreScan points and lab-measured P1 at the 1.6 ha points. A map was generated using inverse distance squared with a 33 m search radius for both lab-measured P1 and IR-estimated P1. In this simplified approach to the Pedogenic Enhanced Grid Sampling, radii were arbitrarily set and no "field average" amount was included. To evaluate the accuracy of the method, the interpolated lab-measured and sensor-estimated P1 was compared to using only the interpolated lab-measured P1 at the 25 validation points. To compare those results with conventional interpolated grid samples, the P1 measured at the 1.6 ha grid samples was interpolated using a 150 m search radius and the interpolated estimate compared to the measured P1 at the 25 validation points. Results show a 35% lower RMSE for including the pedogenic relationship between IR and P1. Maps of each estimate illustrate the additional detail and lowered error of adding data at the .4 ha points. (Figure 7).

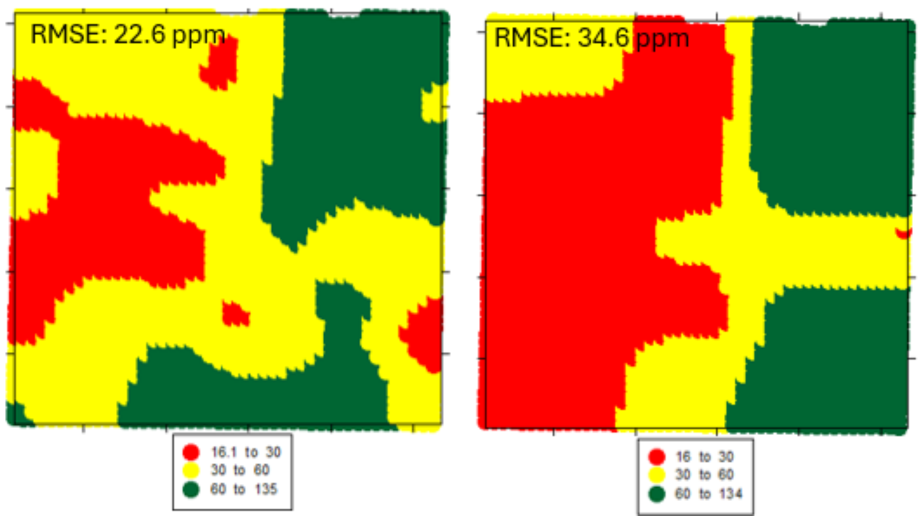

Figure 7. Pedogenic Enhanced Grid Sampling (left) and conventional grid sampling (right).

A machine learning approach was developed using all P1 samples from all 10 fields, excluding the 25 validation points on WCB2, and using that estimate at the .4 ha points rather than the in-field calibration. That exercise yielded an even lower RMSE: 20.2 ppm. The acceptable accuracy level needed to provide useful information is open to debate. It's possible the improvements over conventional grid sampling estimates would be enough to divide the field into low, medium, and high application ranges. It would be more probable to classify into two ranges, suggesting "ok to apply P" and "don't apply P". Another consideration, especially from both economic and environmental perspectives, is the magnitude of errors. Comparing estimated P1 to actual P1 at the 25 validation sites, conventional grid sampling had significantly more potentially harmful errors than the Pedogenic Enhanced Grid Sampling (Table 7).

Table 7. Number of validation sites with major errors

Error (ppm)	Conv. grids	% of field	P.E.G.S.	% of field
>30	8	32%	4	16%
>60	4	16%	0	0%

Conclusions

To investigate the potential of using soil sensing technology to improve grid sampling estimates of key nutrients, 10 fields in five US states were probed with a CoreScan multi-sensor probe and grid samples of two primary nutrients and pH were lab-analyzed. In-field correlations between lab samples and EC, optical, moisture, and compaction measurements in the 0-60 cm profile revealed that all evaluated soil chemical properties had a correlation coefficient above .50 *r* on 7 out of the 10 fields. Multi sensor measurements were more frequently highly correlated than measurements from a single sensor. A machine learning (ML) technique was applied to the dataset with the goals of uncovering and utilizing soil-nutrient relationships, and to reduce soil sampling and analysis costs. While ML improved the correlation coefficients, results showed in-field relationships provided greater accuracy for these fields. The use of machine learning will continue to be investigated. A novel concept, termed Pedogenic Enhanced Grid Sampling, which uses a combination of interpolated grid samples, soil-based nutrient estimates, and field average levels was presented. An example field where this approach was tested using independent validation samples, showed a 35% reduction in P1 estimation errors and an elimination of the largest potentially economically and environmentally harmful errors versus conventional grid sampling. Additional research with additional fields, large datasets that include validation samples, and machine learning is needed to fully develop the Pedogenic Enhanced Grid Sampling approach.

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