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You Can't Manage What You Don't Measure

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Abstract

Soil analysis, and the subsequent methods used to undertake that analysis is a domain of agriculture that has not undergone much change in the last several decades. Most of the analytical methods we still use were developed using "wet chemistry" means and this is largely still true today. However, these methods are difficult, costlty and time consuming. Additionally, there is variability in the results that is introduced by several individuals whom handle the sample and complete the analysis. Every step from the collection and storage of the soil sample, the production of reagents, to the accuracy of the measurement of soil mass, reagent volume, spectrophotometric measurement, and use of proper standards. This variability is hard to control for, yet researchers and producers trust these analysis almost completely. We suggest that a hyperspectral (visible and near infared) reflectance approach, using machine learning and correlative datasets could be a way to remove much of this variability and provide a much more cost effective, spatially relevant solution that would revolutionize precision agriculture. Herein, our approach is discussed.

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Materials and Methods:

Soil samples were collected on site in a grid spaced throughout a field in Northwest Montana at the appropriate timing and in the agricultural cycle such that representative levels of Nitrogen (N), Potassium (K) and Phosphorous (P) were present. The samples were homogenized then scanned in the field using an Malvern Panalytical ASD LabSpec Hi-Res4 spectrometer (covering the range of 400-2400nm). These samples were also then placed in sealed paper bags, then sent to KSI Laboratories to have the nutrient levels measured using Mehlich 3.

Keywords.

- Proximal Spectroscopic Reflectance (PSR)
- Precision Agriculture (PA)
- Spatial Data Density (SDD)

Introduction

The problem of variability in soil nutrient analysis has been studied for years by many industry experts and academics; so far, they have been unable to decipher and successfully commercialize hyperspectral (visible and near infrared, 350-2500nm) soil sensing. Many studies have undertaken years of testing to account for the variability that has a dramatic impact on the precision of resulting recommendations. The main tradeoff we have identified is between accuracy of testing parameters and actionability or usefulness of collected soil data at the field scale. The primary deficiency in most soil analysis data is in the lack of sufficient data to show across-field variability and identify trends and "problem" areas. Understanding where amendment needs to be applied is a central theme of precision agricultural practices that gives them value(Ferguson et al., 2015; Mueller et al., 2001; Schloeder et al., 2001). Traditional soil testing is too prohibitively expensive, in time investment as well as analysis cost, to accomplish this. Greater quantities of granular raw data (more samples/unit area) are required to generate more accurate recommendations in a timely fashion, resulting in improved precision applications

(Mueller et al., 2001). Acquiring large data sets using traditional soil analysis is prohibitively expensive. Test prices vary by lab, region and nutrients tested. In the US alone, tests can vary from $6.00 to $65.00 and generally do not include nitrogen analysis which can cost an additional $15-35.00 in the US; other countries have basic soil tests costing upwards of $135 USD(Court Hill Farm Research Ltd, 2022; UC Davis Analytical Lab, 2022; Wallace Labs, 2022). Hyperspectral imaging provides a lower costs solution resulting in more data points, dramatically increasing efficiency and precise input recommendations. Data resolution being improved, cost is lowered; all while accuracy remains highly corelative to lab results. "Big Data" approaches are often associated with multiple inter-related data sets (weather/climate, chemical soil tests, satellite imaging, LIDAR, yield monitoring, etc.) being leveraged to understand trends and more accurately predict outcomes. Significant computing power to model this data, validation with diverse cropping systems data sets or "ground truthing", and a lot of time is required to create products that are genuine, and actually make precision agriculture, more precise. To farmers and land managers, reliable data is essential to manage performance and identify areas of improvement. Even with all the best algorithms and data analysis techniques, models are only as good as the data that is used to create them. Hyperspectral soil analysis provides a cost-effective method to obtain far more data sets per acre (increased data density per unit area) for a much lower net cost to the grower, compared to traditional soil analysis methods. In one Montana trial, we acquired 81 data sets versus 3 data sets for the same cost (Hubbard Field Trial 2018-2021). More soil samples aren't the solution, precise and actionable data is the solution.

Identifying the Problem with Traditional Soil Testing

Soil analysis and subsequent nutrient management has always been an area pivotal to the productivity of cropping systems. Accurate prescription maps are essential for effective variable rate fertilization (Ferguson et al., 2015; Sawyer, 1994). Grid soil sampling has most frequently been used to develop these prescription maps (Mueller et al., 2001). Past research has indicated several technical and economic limitations associated with this approach. There is a need to keep the number of samples to a minimum (to control cost) while still allowing a reasonable level of map quality. However, Gotway et al. found that the optimum grid density may depend on the coefficient of variation in the field in question (1996). In many cases, where the spatial distribution is complex, much finer grid densities than those currently used commercially are required to produce accurate prescription maps. Tillage, field leveling, and rainfall events can reorganize soil horizons and result in exposed sub-surface horizons, buried surface horizons, mixing of horizons, and most importantly, loss or movement of the A and B horizons. These horizons are the most productive, fertile, have the highest water holding capacity in most soils. Understanding these edaphic trends across the field using a user-friendly and intuitive interface, farmers can specifically target "problem" areas, as well as understand where yield potential is likely to be highest. Research by Mueller et al. has indicated that a common commercial grid sampling scale of 100 m^2 was grossly inadequate and that soil sampling at greater densities only modestly improved prediction accuracy that would not justify the increase in sampling cost (2001). Their data suggest that the use of the field average fertility values at their research field was not substantially different than grid sampling. Schloeder et al. demonstrated that spatial interpolation was usually inappropriate for grid sampled data with limited sample size (n = 46) (2001). For most of their data sets the inability to accurately predict, could be attributed to either spatially independent data, limited data, sample spacing, outlier values, or unusually high sample variability probably attributed to inadequate understanding of the source(s) of variability. Research by Whelan et al. reported that in fields with less than 100 samples only very simple geostatistical interpretation methods such as inverse distance are appropriate (2015). Sample sizes of 100 to 500 are needed for geostatistical methods such as kriging. Kravchenko and Bullock, studied several interpolation techniques, such as ordinary kriging, lognormal kriging, and inverse distance weighting, and found the best geostatistical methods to use depend on unique spatial properties in each field and could not be predicted in advance (1999). Research by McBratney and Pringle, reported that grid sampling at 20 m^2 to 30 m^2 scale is generally needed when applying site specific management at a resolution of 20 m^2 (1999). Mallarino and Wittry (1997) reported that cells larger than 0.8 ha in size usually did not represent nutrient levels precisely (1997).

Methods for Detecting Soil Nutrients Using Hyperspectral Sensors.

Using advanced algorithms Soilytics® can convert hyperspectral reflectance data into usable information to serve the agricultural industry and potentially help us better understand the variability of soils in a more robust way over time. A Malvern Panalyticals ASD LabSpec was used to collect relevant data for the work, although off-the-shelf imaging equipment was used, the spectra wavelength and application are the result of several years of internal research and development. The sensor includes the hyperspectral sensor with contact probe, computer, and fiber optic cable (specifications in Table 1 below).

Table 1 - Hyperspectral Scanner Properties - Malvern Panalytics ASD LabSpec (date and model number)

Wavelength range	350-2500 nm
Resolution	3 nm @ 700 nm
	6 nm @ 1400/2100 nm
Scanning time	100 milliseconds
Signal-to-noise ratio	
Visible Near Inferred	9,000:1 @ 700 nm
Short Wave Inferred 1	9,000:1 @ 1400 nm
Short Wave Inferred 2	4,000:1 @ 2100 nm
Photometric noise	
Visible Near Infrared	4.8 x 10-5 AU or 48 µAU@ 700 nm
Short Wave Infrared 1	4.8 x 10-5 AU or 48 µAU@ 1400 nm
Short Wave Infrared 2	1.1 x 10-4 AU or 110 µAU@ 2100 nm
Visible Near Infrared detector	(350-1000 nm) 512 element silicon arrays
Short Wave Infrared 1 & 2 detectors	(1001-1800 nm) & (1801-2500 nm)
	Graded Index InGaAs Photodiode,
	TE Cooled

The sensor must have a minimum operating range of 350 nm to 2500 nm to result in the most comprehensive results and the best correlation to soil parameter values. Compressed

Polytetrafluoroethylene (PTFE) White reference tile is used as a control to normalize reflectance data from the sensor at each sampling event with a minimum number of scans to assure that baseline is stable, and equipment is functioning within acceptable parameters. There are abiotic factors that our data shows have a strong impact on the precision and noise level of data acquired. These are: texture, water content, and minerology (especially clay content and clay minerology). The spectral reflectance data once collected, must be normalized based on these factors as they have significant impact on results. This also means that results concerning texture, water content, and minerology are significant results on their own and can be very useful when creating a management strategy. For instance: texture and clay type can give clues about availability of certain cations and can provide information after being combined with pH data to inform nutrient availability. The variability of water content across the field when combined with texture and minerology data can point to areas in the field that are more likely to cause water stress or be particularly good at infiltrating or storing water or provisioning nutrients into the soil solution. After these abiotic factors have been properly controlled for the baselined data can then be processed into heat maps and actionable prescription maps (See Figure 1). From this data we have determined that use of the wavelength range of 350-2500 nm have resulted in the best prescription map outcomes and improved efficiencies for the farmer or land manager. We have seen excellent results especially with pH measurement and subsequent lime application in forage systems in Montana (Hubbard Field Trial, 2018-2021). Since limiting factors on confidence required additional spectral bands to properly baseline. Hyperspectral technology allows for quick

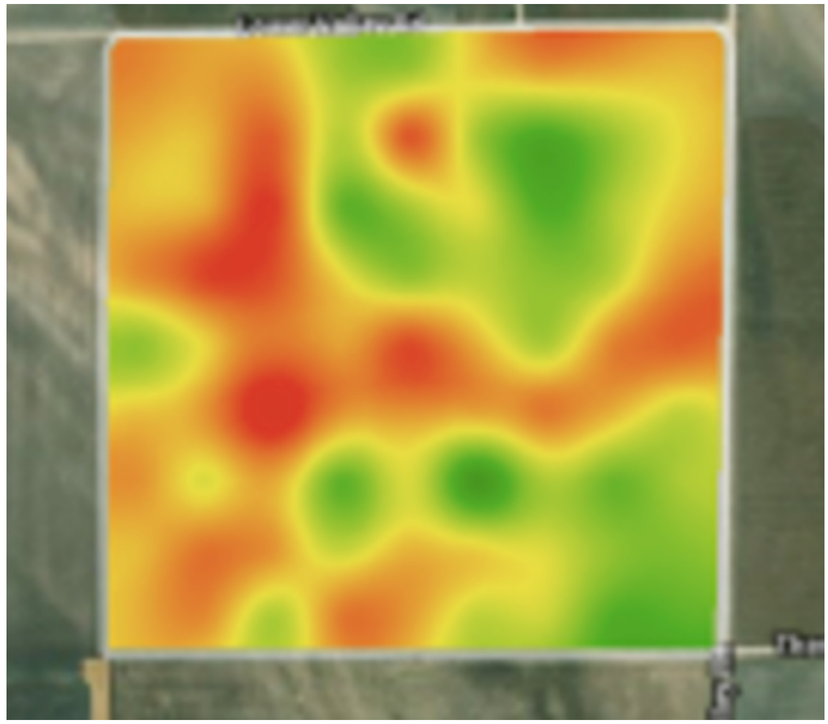

Figure 1 Example heatmap generated from hyperspectral imaging and Soilytics analysis for pH in Marshall Field Trial (2020-2021)

and easy data processing at a cost-effective rate. The sample data can then be uploaded directly to the labs or farm equipment for rapid decision making and proactive farming decisions while eliminating delays caused by collection, shipping, and analysis compared with traditional lab tests. It will serve the precision agricultural market by improving fertilizer application and efficiency. Our technology will help farmers increase and reduce the variability of crop yields, optimize input costs, and improve environmental protection by reducing unnecessary fertilizer applications.

Results and Discussion

Internal Trial 1 – Hubbard Field – The Promise of Hyperspectral Approaches

An internal trail with a forage production operation in the Hubbard Field Trial in Montana resulted in a lime application to neutralize acidic soils for improved plant growth (2018-2021). Lime was applied on 107 acres vs 220 because of more precise pre-application pH data sets to predict the variable spread of the lime.

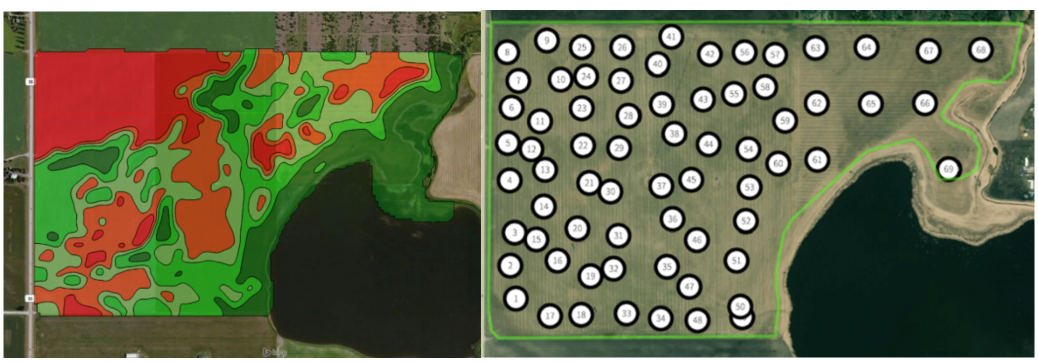

Figure 2 - Map of soil zones (n=37) used to predict pH in the Hubbard field trial 2018-2021 (left) density of data points (n=69) collected using hyperspectral approach resulting in heat map for precision lime application (right)

The savings generated using hyperspectral soil analysis was $21,879 in lime, $1,739.75 in lab analysis. Meanwhile the grower received 69 sample points rather than 37 sample points. Cost savings is only part of the value, Crop Productivity Index (CPI) or a measure of the variability of yield from year to year with 100 being the mean value for that cropping season. The results for CPI in the Hubbard field Trial were:

2018 – 24-point difference (improvement) in CPI values

2021 – 4-point difference (improvement) in CPI values

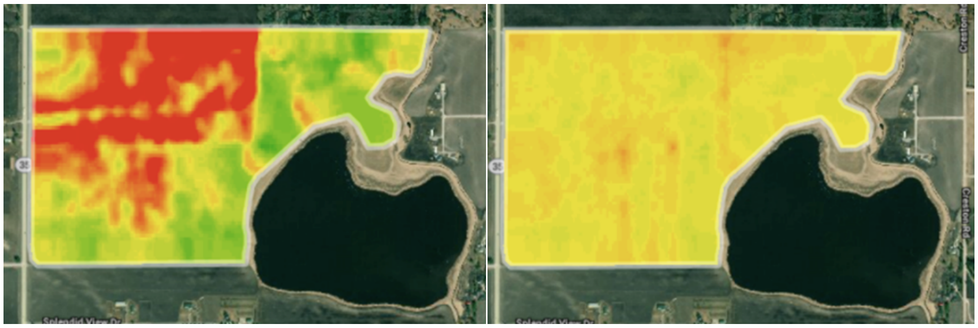

Figure 3 - pH heatmap created using hyperspectral approach (Left) vs heatmap previously used using zoned sampling approach (Right).

The change observed was from over 47% of the field with below optimal pH in 2016 to 1.6% of the field below optimal in the 2021 growing season. A more recent internal trial also observed a dramatic increase in nutritional value (including protein content) of the forage crop after improved data was used to apply nutrients. However, some of this improvement may be due to other covariables such as seed genetics, climatic conditions, and pest load.

Internal Trial 2 – Marshall Field – Eliminating Limiting Factors

An internal trail with a forage production operation Montana (Marshall Field Trial 2020-2021) resulted in a sulfur application to help balance pH. The field was 160 acres previously planted in hay. Application maps had previously been zone sampled based on NDVI satellite imagery for multiple years of data. When mapped using hyperspectral approaches and the Soilytics® platform, 81 data sets generated made managers able to easily see that the zoned areas did not coincide with actual nutrient levels across the field. The addition of more data density (3 zones previously to 81 data points after hyperspectral imaging) resulted in much better precision application now being possible.

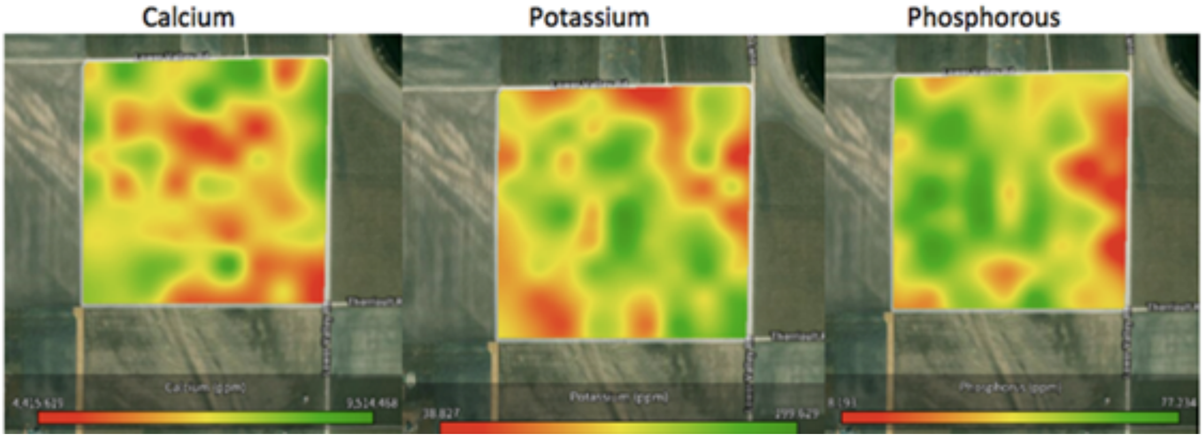

Figure 4 - Heat-Maps of plant essential nutrients created using hyperspectral imaging and 81 data points (Marshall Field Trial 2021).

According to Liebig's law of minimums, plant health and associated yield are limited by the scarcest essential nutrient (limiting factor) which is analogous to the requirement of amino acids in the human diet (von Liebig, 1850). Using a cost-effective way to not only determine the precise levels of nutrients and how much to amend a field is valuable but understanding the spacial distribution of the nutrient in question or areas where it might be totally lacking, we expect would be an even more powerful and effective tool. Imagine a flood or land-leveling event took place and the manager wants to understand how nutrients might have been moved or removed from the field or where they might have been deposited. Using this approach might be a cost-effective way to survey the relative levels of essential macro and micro-nutrients and determine if certain areas of the field need amendment without wasting money and time amending the whole field "just to be safe." Improving these types of decision scenarios is the main promise of this technology from our vantage point. In the Marshall field trial discussed above, the agronomist in charge was able to make a better determination of the limiting factor in the field and determined that the sulfur application was the best solution to lagging yields. With the variable application the farmer was able to save $1,310 in input costs and decreased 3.7 tons in fertilizer volume. Variable rate application vs. applying flat-rate saved the grower $13.06/ac. Identifying the area of need across the field enabled greater uniformity yields and increased overall crop production.

Internal Trial 3 – The Future Promise of Hyperspectral Approaches

The ability to correctly use variable rate technology will depend on testing methods to determine how the 4R's (*Right Source, Right Rate, Right Place and Right Time*) are applied to a field (Savidge & Geisseler, 2022). The ability to use hyperspectral data for more detailed mapping of nutrients can help save farmers money without risk of lagging yields by better defining fertilizer application areas. The savings resulting from variable rate technology on 7 fields once (see Table 2 below) again proves years of trials showing that more granular testing results in lower net-costs and higher yields. Hyperspectral technology using the Soilytics® method can help reduce lab costs even more while providing many if not all the benefits we have discussed.

Table 2 - Economic Savings from field trials using Soilytics and hyperspectral approach.

	TRADITIONAL		SOILYTICS		SAVINGS		
Field A	$	5,636	$	5,442	$	194	3%
Field B	$	3,628	$	2,574	$	1,055	29%
Field C	$	17,805	$	10,968	$	6,837	38%
Field D	$	11,499	$	11,331	$	168	1%
Field E	$	6,801	$	6,233	$	568	8%
Field F	$	10,100	$	8,992	$	1,108	11%
Field G	$	62,412	$	51,233	$	11,179	18%
Average	$	19,646.76	$	16,128.87	$	3,517.89	18%

Summary

As we continue to demonstrate, no one grid size or interpolation technique perfectly describes the soil nutrient/pH variability that exists in any field. If one fails to sample at a fine enough resolution to capture the spatial correlation in crop nutrient data, the interpolation methods and application maps developed from those methods will not be valid or accurate (Reich, 2000). However, the cost associated with grid sampling to the intensity required for accurate maps is prohibitive for chemical analysis in many cases, whereas the use of hyperspectral soil analysis is much more economically efficient.

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This paper was the original work of the authors and was completed with internal research by Precision Data Mining team, its employees, and designees for the purpose of sharing knowledge

of hyperspectral approaches to soil analysis and interpretation. We believe that giving more information to farmers to empower their decision making is not only an economic benefit to them, but also has the promise to improve the environment by reducing the externalities inherent in some agricultural practices.

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