Hyperspectral Sensing for Soil Health

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***Abstract*—Soil nutrient mapping has been implemented in agriculture for the last 40 years. Ongoing economic pressures in agriculture to increase crop yields while sustaining farmer profitability demands in-depth knowledge of soil nutrients. Spatial and temporal variability of yield-limiting factors have been recognized for a long time, and, with such information, farmers have technologies to manage their fields site-specific. However, farmers still tend to manage their fields uniformly because it takes cost, labor, and money to assess and monitor soil health conditions by traditional lab-based methods. We have used a rapidly emerging hyperspectral sensing technology to assess plant-available nutrient content in soil, especially nitrogen, for the use of optimizing in-season nitrogen management. The new and emerging technology would empower farmers with data to help them make better decisions to grow more profitable crops, protect the environment, while growing more nutritious food**

Keywords—Proximal spectroscopic reference, precision agriculture, spatial data density

I. Introduction

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. The ability to standardize and commercialize hyperspectral (visible and near-infrared, 350-2500 nm) soil sensing is an effort that is recognized by the FAO (Food and Agricultural Organization) of the United Nations. This is due to its inexpensive method and ability to give more spatial and temporal data per field than traditional wet analysis in a timely manner [1] (Mahajan et al. 2014, 499-522). Many studies have undertaken years of testing to account for the variability of various soil tests and nutrients that has a dramatic impact on the precision of resulting recommendations [2,3,4]. The primary deficiency in most soil analysis data is the lack of sufficient data to show across-field variability and identify trends and areas of action. Understanding where, when, and how much nitrogen or other nutrients and in which form is required for crop growth depend on field management, weather conditions, topography, and soil health, and thus understanding spatial and temporal variability of soil nutrient is one of the central themes for precision agricultural practices [2,3,4]. Traditional soil testing is too prohibitively expensive in terms of time investment and cost, and many farmers have hesitations to regularly test soil nutrients, particularly soil nitrogen, due to the high spatial and temporal variability within a field.

Soil nitrogen is vulnerable to volatilization or leaching, and the accuracy of testing has been under scrutiny from the aspects of sampling methods, depths, and the handling of soil samples for analysis. A key temperature requirement for nitrogen volatilization of the sample is 67 degrees F. Data quantities of granular raw data (more samples/unit area) are required to generate accurate recommendations in a timely fashion, resulting in improved precision applications [3]. Acquiring large data sets using traditional soil analysis is prohibitively expensive. Soil test prices vary by lab, region, and forms of nitrogen to be tested. In the U.S. alone, standard soil tests may vary from $6.00 to $65.00 per sample and generally testing nitrogen analysis require an additional cost of $15-35.00 per sample [5]. Other countries have basic soil tests costing upwards of $135 USD.

Hyperspectral soil sensing provides a lower cost 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 correlated to lab results. "Big Data" approaches are often associated with multiple interrelated data sets (weather/climate, chemical soil tests, satellite imaging,

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LIDAR, yield monitoring, etc.) being leveraged to understand trends and more accurately predict soil properties. Yet, significant computing power to model this data and validation with diverse cropping systems data sets or "ground truthing"are required to be precise and practical for accurate prediction of soil health properties for precision agriculture. To farmers and land managers, reliable data is essential to manage performance and identify areas of improvement.

II. Identifying the Problem with Traditional Soil Testing

Soil analysis and subsequent nutrient management have always been an area pivotal to the productivity of cropping systems. Accurate prescription maps are essential for effective variable rate fertilization [2] . Grid soil sampling has most frequently been used to develop these prescription maps [3]. Past research has indicated several technical and economic limitations associated with this approach. There has been a need to keep the number of samples to a minimum (to control cost) while still allowing a reasonable level of map quality. However, the optimum grid density may depend on the coefficient of variation in the field [6]. In areas where the spatial distribution of soil properties is complex, much finer grid densities than those currently used commercially are required to produce accurate prescription maps. By understanding these edaphic trends across the field using a user-friendly and intuitive interface, farmers can specifically target "problem" areas where yield potential is likely to be high. Reference [3] 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 which would not justify the increase in sampling cost . Reference [4] demonstrated that spatial interpolation was usually inappropriate for grid-sampled data with limited sample size ($n = 46$) . This was further proved in our 2021 study using 56 samples from one field in each of the summer and fall testing periods. For most of their data sets, the inability of accurate prediction 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. In fields with less than 100 samples only very simple geostatistical interpretation methods such as inverse distance are appropriate. Sample sizes of 100 to 500 are needed for geostatistical methods such as kriging. Kriging is one of several mathematical methods which involves a limited set of sampled data points to estimate the value of a variability over a continuous spatial field. 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. Areas larger than 8000m^2 in size usually do not represent nutrient levels precisely. The phase II results mentioned in this report will show our findings on the relationship between the number of samples and prediction accuracy and highlights that variations in test methodology and practices will impact the correlation to traditional methods when reporting the test results.

III. Methods for Detecting Soil Nutrients Using Hyperspectral Sensors/Spectroradiometers.

Soil spectroscopy uses advanced algorithms to convert hyperspectral reflectance data into usable information to serve the agricultural industry. A Malvern Panalytical ASD FieldSpec was used to collect relevant data for the work in this study. The equipment includes the hyperspectral sensor, contact probe, computer, power cables, and fiber optic cable (specifications in Table 1 below).

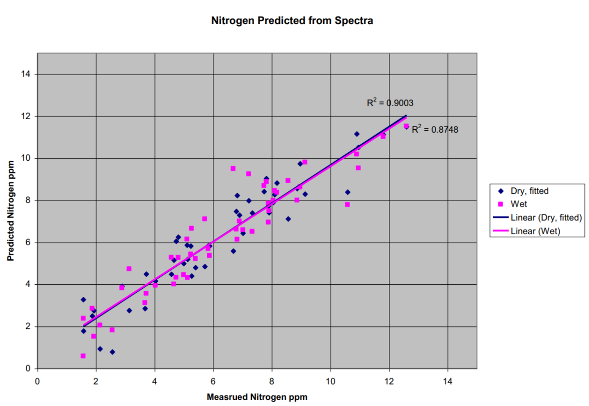
TABLE I. Hyperspectral Scanner Properties of Malvern Panalytical ASD FieldSpec

Wavelength range	350-2500 nm
Resolution	3 nm @ 1400/2100 nm
Scanning time	100 milliseconds
Signal-to-noise ratio	
Visible Near Infrared	9,000:1 @ 700 nm
Short Wave Infrared 1	1 9,000:1 @ 1400 nm
Short Wave Infrared 2	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@ 700 nm
Short Wave Infrared 2	(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 produce 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 ensure that the baseline is stable, and equipment is functioning within acceptable parameters. There are abiotic factors that have a strong impact on the precision and signal to noise level of data acquired, including texture, water content, and mineralogy (especially clay content and clay mineralogy) However these factors can be very useful when creating a management strategy. For instance: texture and clay type can give clues about the 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 mineralogy 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.

These abiotic factors have been properly controlled for the baselined, data can then be processed into heat maps and actionable prescription maps. Hyperspectral technology allows for quick and easy data processing at a cost-effective rate. The sample results can be uploaded directly to the labs or farm equipment for rapid decision-making and proactive farming decisions while eliminating delays and chemical changes to samples caused by the collection, shipping, and analysis compared with traditional lab tests. It will serve the precision agricultural market by improving fertilizer application and efficiency. This technology will help farmers increase and reduce the variability of crop yields, optimize input costs, and improve environmental protection by reducing unnecessary fertilizer applications.

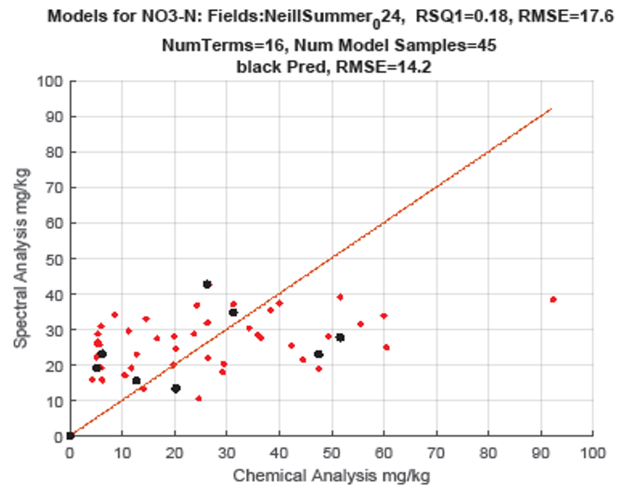
The initial proof of concept involved collecting soil samples on-site in a 4-acre grid spaced throughout a field in west central Illinois at the correct time in the agricultural cycle resulting in all levels of Nitrogen (N), Potassium (K), and Phosphorous (P) being present. The samples were stored in sealed paper bags, then sent to Waters Agricultural Laboratories to have the levels of N, P, K measured. The samples were then sent to SpecTIR to be assessed in their lab environment using spectrometry techniques. The samples were separated into two equal groups, and the first group was then air-dried. The moisture content of each group was not measured. SpecTir utilized two hyperspectral sensors (covering the range of 400-2400 nm) in controlled halogen lighting conditions (700 Watts, approximating daylight levels per square meter), and the samples were passed under the sensors. The end result, after calibration of the sensors for both white reflectance and dark (no reflectance) values and spatial averaging over the sample area, was a spectral signature for each of the 48 samples and at both the "as sent" and the "air dried" water levels.

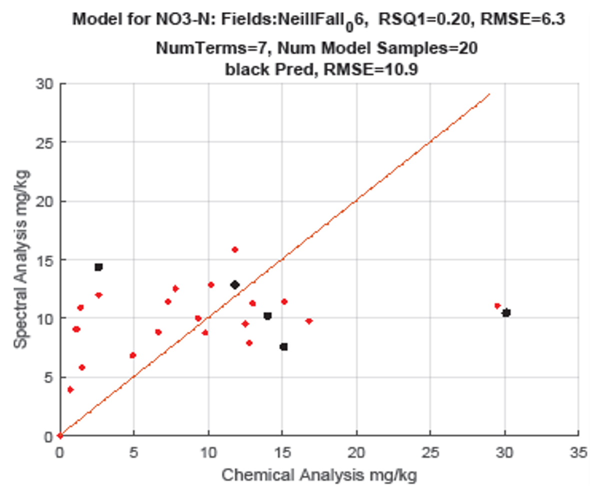


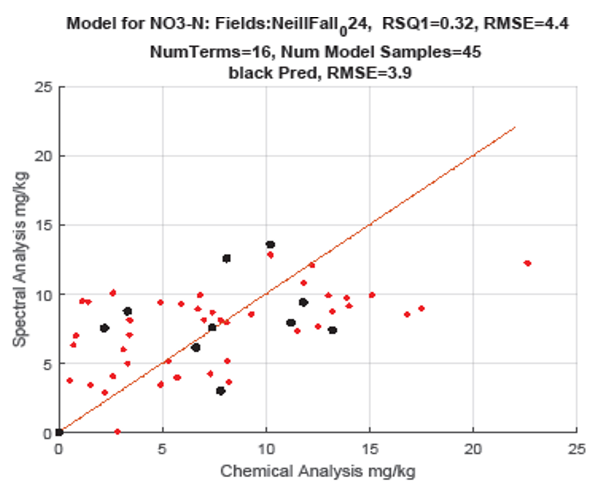
IV. Results and Discussion

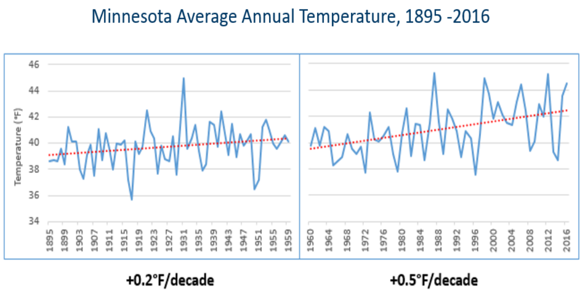
A. Trial One in 2021 – One field in Minnesota – The Promise of Hyperspectral Approaches

A phase I trial with corn production operation in one field resulted in our urea application for improved yield response (2021). It was determined from this study that the use of 27 samples is too few to build good models. Improvement may be dependent on a larger sample size or other co-variables such as climatic conditions and sample handling. The testing of deeper samples was further substantiated by factoring in the weather data for sampling at a greater depth in the fall during cooler temperatures showed a higher correlation to lab testing and a lower root mean squred error (RMSE) value with a validated explanation that shallow- incorporated urea is subject to volatilization losses as ammonia gas.









B. Trial Two – Seven Fields in Minnesota – Increase sample size for better model building

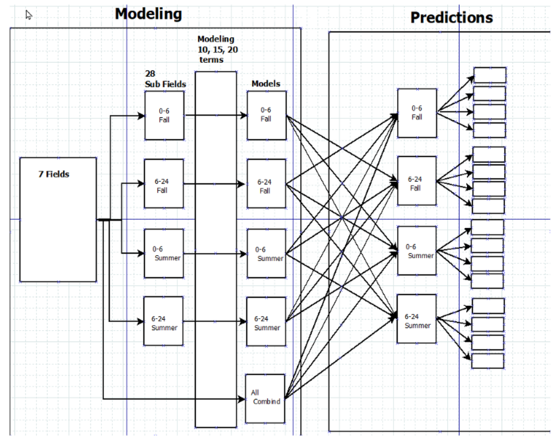
An internal trial was conducted on-farm with a corn production operation in Minnesota where soybean was planted a year before. In a previous study, it was determined that the zoned areas did not coincide with actual nutrient levels across the field [7]. Using a cost-effective way to determine the precise levels of nitrogen application and site-specific distribution is essential to a farmer's cost, yield, and potential environmental impact from excess nutrient overload on the surface and into groundwater. In an independent study on the Marshall field trial discussed above, the agronomist in charge was able to make a better determination of application as the best solution to lagging yields. With the variable application, the farmer was able to save \$21,879 in input costs and \$1,739.75 in lab analysis. Identifying the area of need across the field enabled greater yields and increased overall crop production.

2018 – 24-point difference in CPI (crop productivity index) values

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

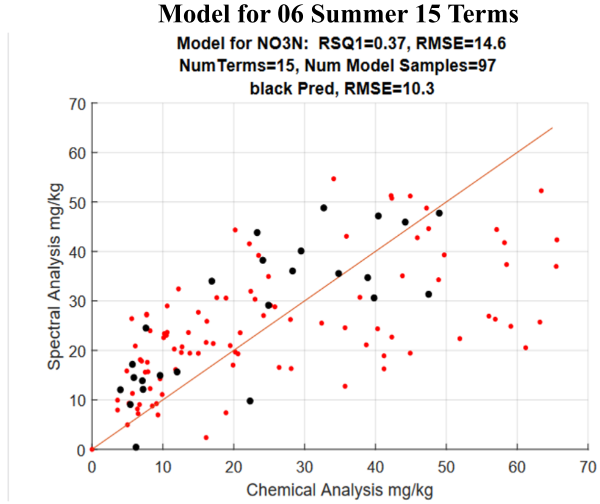
2022 –2.5-point difference(improvement) in CPI values with increased yields

The results from the seven fields resulted in promising results. The Minnisota study had larger variations in correltion from our original test methods in this study which could have been caused by the change in test method from air dried in the preliminary study to heat dried and sieved in the laboratory for the phase I and phase II studies. There were large value variations between samples, fields, and temperature conditions. The model building plan was designed to investigate differences in weather conditions (ambient field temperature) and sample depths. The following model plan was used to compare the best practice for creating models and test methodology.

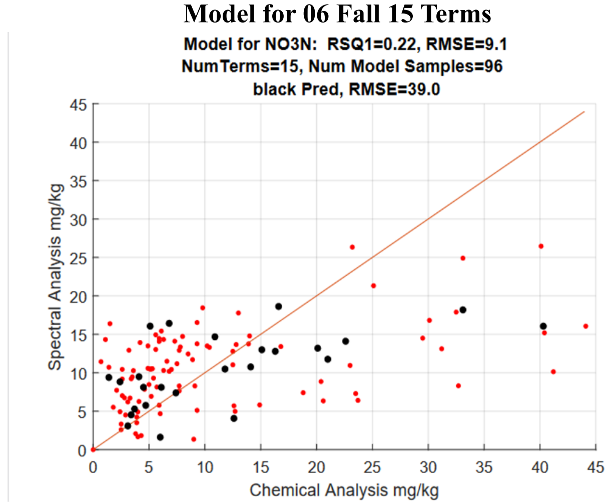


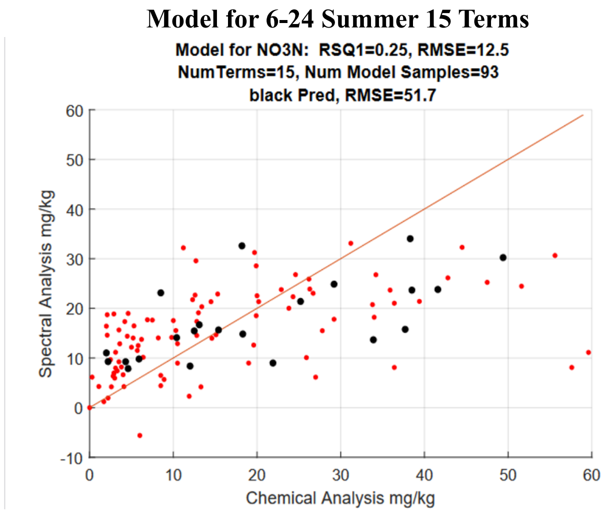
Models were generally reasonable under the post-processing methods used in sample preparation. The results were generally poor predictions when using one condition (Summer, Fall, 0–6",6–24") to predict another condition. The result from 0–6-inch samples to 6–24 inch samples provided improved results over those created from season to season alluding to ambient air temperature effects on nitrogen readings. The use of models created from all fields combined does a reasonable job of predicting individual seasons or conditions.

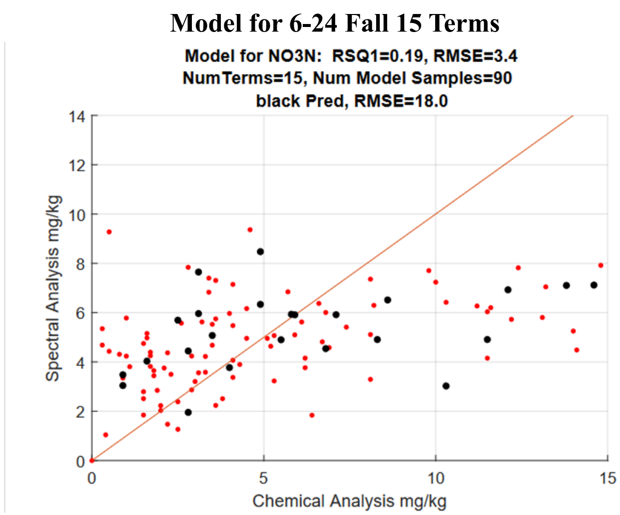
Model for 06 Summer 15 Terms



Model for 06 Fall 15 Terms







V. Summary

Nitrogen hyperspectral soil sensing is essential to develop a cheaper and faster testing method with accuracy. The technology continues to show great potential for testing nitrogen for better application accuracy and further usefulness in reducing input costs for farmers and reducing nutrient overload in our waterways through integrated precision applications.

Testing conditions for volatile substances like nitrogen should be further investigated to reduce user error and variations caused by volatility as a result of field conditions. Using the hyperspectral soil sensing approach can 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. Overall resulting in conserving resources as only the areas that need attention will be addressed. Improving the method and decision scenarios to improve testing accuracy and granularity is the main promise of this technology.

Phase III infield testing using spectroscopy, west lab chemistry, and post-processed spectroscopy is essential to eliminate the variables of accuracy due to sample degradation that results from nitrogen volatility at temperature. Evaluating nitrogen status in soil before planting and during the growing season has benefits to prescribing nitrogen only required for in-situ crop growth. The ability to use hyperspectral data for more detailed mapping of nutrients can also save farmers money and time by defining the right place, right amount, and right type of fertilizer needed in a given area based on more detailed nutrient application maps. Years of trials in different regions, different soil textures, mineralogy, and climate would be important to prove the infield use of assessing soil nitrogen availability.

Acknowledgment

We extend our thanks to the Department of Water and Soil at the University of Minnesota for participating in the research.

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