Changing the Cost of Farming: New Tools for Precision Farming

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Abstract. Accurate prescription maps are essential for effective variable rate fertilizer application. Grid soil sampling has most frequently been used to develop these prescription maps. 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 while still allowing a reasonable level of map quality. As can be seen, precision agriculture management requires understanding soil at increasingly finer scales. Conventional soil sampling and laboratory analyses lack this granularity and are time consuming and expensive. Remote soil sensing overcomes these shortcomings. Through its collection of spatial data with quicker, cheaper, and less laborious techniques, remote soil sensing has the opportunity to enhance precision farming today. The objectives of this article are to review the challenges facing conventional soil sampling and evaluate new remote soil sensing tools to enable farmers to better utilize effective solutions to high fertilizer costs and low commodity prices. Soil samples were collected on site in a grid spaced throughout a field in west central Illinois 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 stored in sealed paper bags, then sent to Waters Agricultural Laboratories to have the levels of N, P, and K measured. The samples were then sent to SpecTIR to be assessed in their lab environment using spectrometry techniques. The fundamental conclusion is that it is possible to measure N, P, and K (and probably other desired nutrients/elements) by using a spectrometry genre technology. This was the desired objective of the first milestone and the lab acquisition and subsequent analysis demonstrates the ability to detect the presence and quantify the concentration of N, P, and K in soil.

Accurate prescription maps are essential for effective variable rate fertilizer application (Sawyer, 1994; Ferguson et al., 1996). 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 while still allowing a reasonable level of map quality. However, Gotway et al. (1996) found that the optimum grid density may depend on the coefficient of variation. In many cases, where the spatial distribution is rather complex, much finer grid densities than those currently used commercially are required to produce accurate prescription maps. Mueller et al. (2001) indicated that a common commercial grid sampling scale of 100 m was grossly inadequate and that sampling at greater intensities only modestly improved prediction accuracy that would not justify the increase in sampling cost. Their data suggest that the use of the field average fertility values at their research field was not substantially worse than grid sampling. Schloeder et al. (2001) demonstrated that spatial interpolation of grid sampled data with limited sample size (n = 46) was mostly inappropriate. For most of their data sets the inability to predict, could be attributed to either spatially independent data, limited data, sample spacing, extreme values, or erratic behavior. Whelan et al. (1996) reported that in fields with less than 100 samples only very simple geostatistical methods such as inverse distance are appropriate. Sample sizes of 100 to 500 are needed for geostatistical methods such as kriging. Kravchenko and Bullock, (1998) studied several interpolation techniques, such as ordinary kriging, lognormal kriging, and inverse distance weighting, and found the best geostatistical methods to use depended on unique spatial properties in each field and could not be predicted in advance. McBratney and Pringle, (1999) reported that grid sampling at 20 to 30 m is generally needed when applying site specific management at a resolution of 20 by 20 m.

As can be seen, precision agriculture management requires understanding soil at increasingly finer scales. Conventional soil sampling and laboratory analyses lack this granularity and are time consuming and expensive. Remote soil sensing overcomes these shortcomings. Through its collection of spatial data with quicker, cheaper, and less laborious techniques, remote soil sensing has the opportunity to enhance precision farming today. The objectives of this article are to review the challenges facing conventional soil sampling and evaluate new remote soil sensing tools to enable farmers to better utilize effective solutions to high fertilizer costs and low commodity prices.

Materials and Methods:

Soil samples were collected on site in a grid spaced throughout a field in west central Illinois 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 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 400-2400nm), 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.

Results and Discussion:

SPECTIR Test Results

Figure 1 below is a plot of the spectra for all 48 dry samples. The notable features include the blip at 87 nm is due to the crossover between the VISNIR sensor and the SWIR sensor, has nothing to do with the actual reflectance. The large dips at about 1400 and 1900 are water absorption features. This can clearly be seen in Figure 3 which shows sample 1 both wet and dry. While all the spectra have the same general shape, there is quite a spread in values. Most of the NPK features are fairly fine grain wavelength resolution, not the larger overall level shifts. This larger overall level shift is one of the difficulties facing this project. They are caused by a combination of moisture and soil texture or grain size. In addition, under ambient lighting conditions (as opposed to the test lab conditions), the light level and colo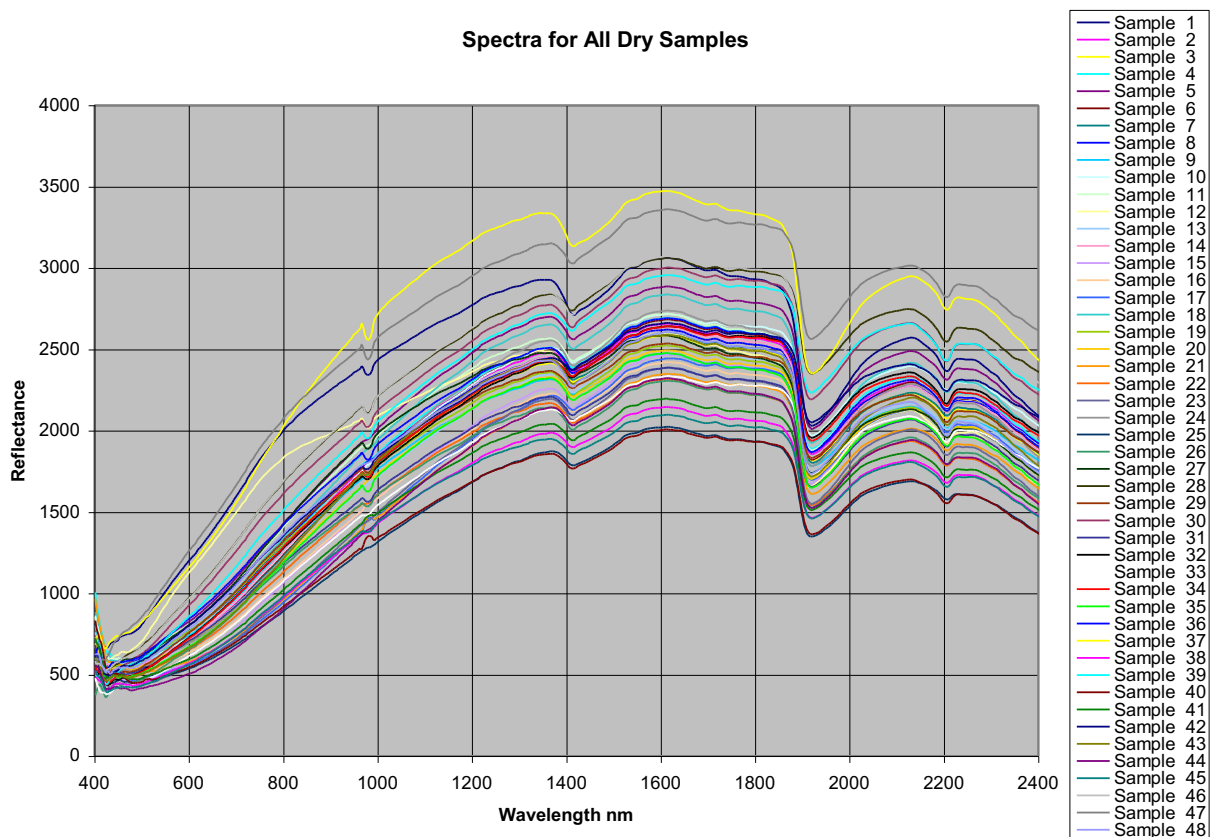r would also contribute to this general shape shifting. In addition, under ambient lighting conditions (as opposed to the test lab conditions), the light level and color would also contribute to this general shape shifting.

Fig. 1 Plot of the spectra for all 48 dry samples

Sample Observations

There is an interesting correlation between the obviously different colored sample 12 and its spectrum as shown below in Figure 2 as a bold yellow trace. There is also an interesting and telling difference between samples 34 and 35 shown below, primarily in the texture or grain size of the samples. The lab measurements of these samples show relatively similar amounts of the N, P, K measurements compared with the overall spread. As shown on the spectral plot below, 35 is the bold red trace and 36 is the bold green trace, and there is a substantial difference in overall reflectance due to the soil texture.
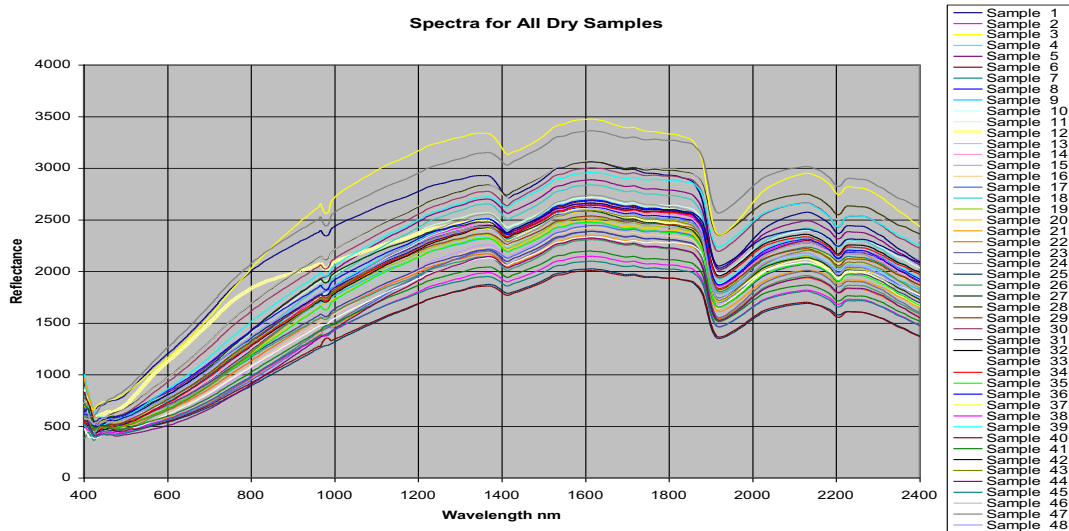
Fig. 2 Sample Observations

The effect of moisture level is highlighted below in figure 3. There is a large drop in signal level with the addition of some level of moisture. The water absorption features at 1400 and 1900 are much stronger with added moisture.
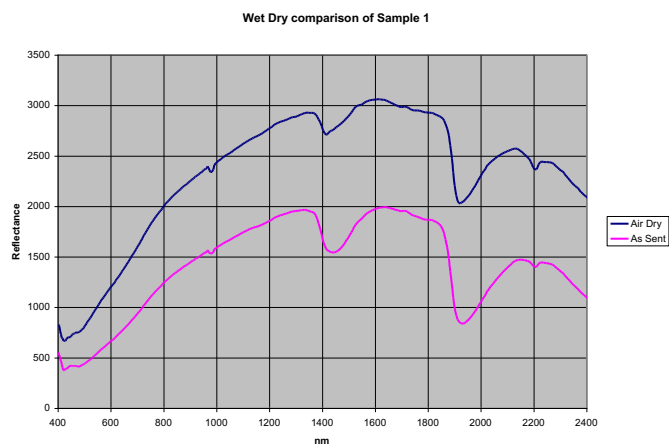
Fig. 3 Wet and Dry Observation

Analysis Methodology

The basic approach was to do a single regression fit for each element, since we have the ground truth values to use for fitting. By doing a simple nonlinear iterative regression, we are able to determine a correlation value for each of the N, P, K elements, and the Ph and Organic Material (OM) levels. This works very well for fitting the dry data, or for fitting the wet data, but it becomes immediately obvious that you cannot predict wet values using dry coefficients or vice versa. The 5 plots below (figures 4, 5, 6, 7, and 8) show the correlation or fit values for each of the 48 samples plotted against their measured values. The blue points are fitting the dry data and the pink are from fitting the wet data.
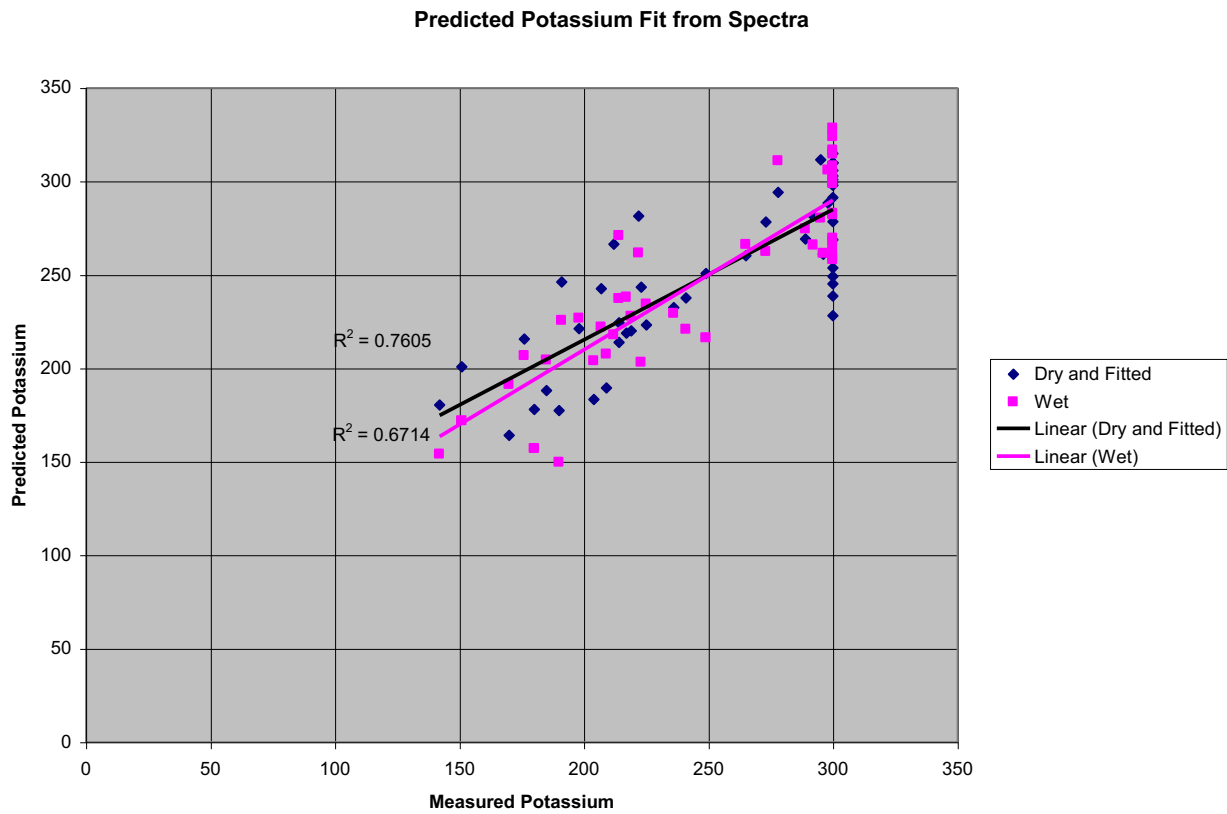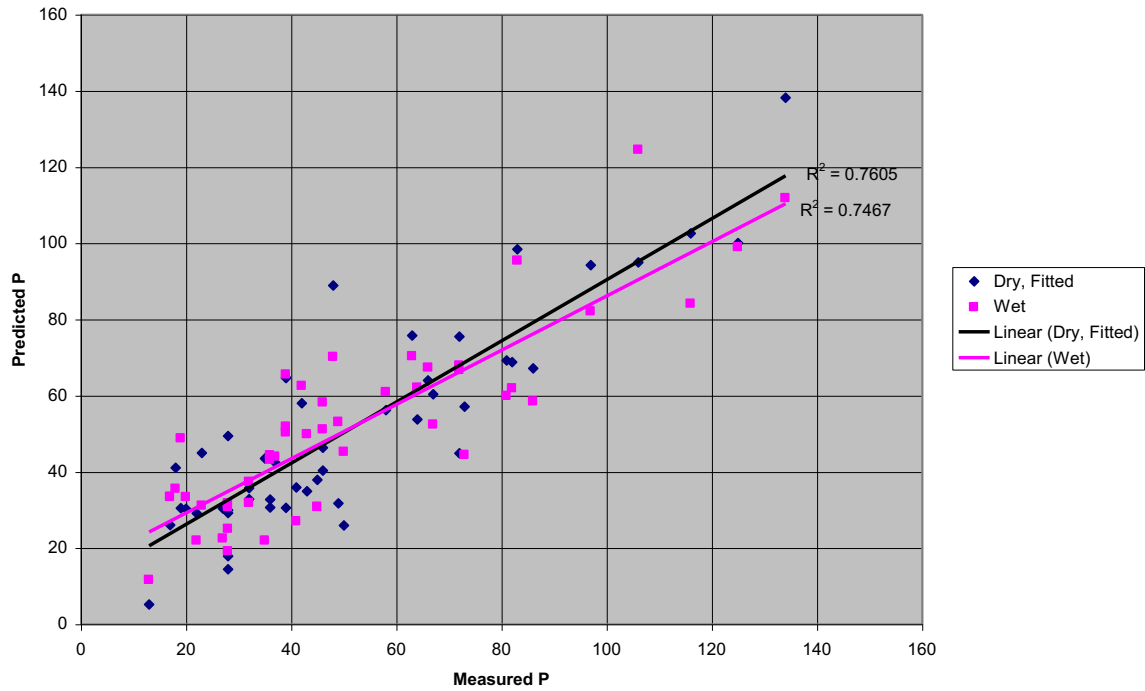
Predicted Potassium Fit from Spectra

$R^2 = 0.7605$

$R^2 = 0.6714$

Legend:
- ◆ Dry and Fitted
- ■ Wet
- — Linear (Dry and Fitted)
- — Linear (Wet)

X-axis: Measured Potassium
Y-axis: Predicted Potassium

Fig. 4 Predicted Potassium Fit

Predicted Phosphorus levels from Spectra

$R^2 = 0.7605$

$R^2 = 0.7467$

Legend:
- ◆ Dry, Fitted
- ■ Wet
- —— Linear (Dry, Fitted)
- —— Linear (Wet)

X-axis: Measured P
Y-axis: Predicted P

Fig. 5 Predicted Phosphorus Fit

Nitrogen Predicted from Spectra

$R^2 = 0.9003$

$R^2 = 0.8748$

Legend:
- ◆ Dry, fitted
- ■ Wet
- —— Linear (Dry, fitted)
- —— Linear (Wet)

X-axis: Measrued Nitrogen ppm
Y-axis: Predicted Nitrogen ppm
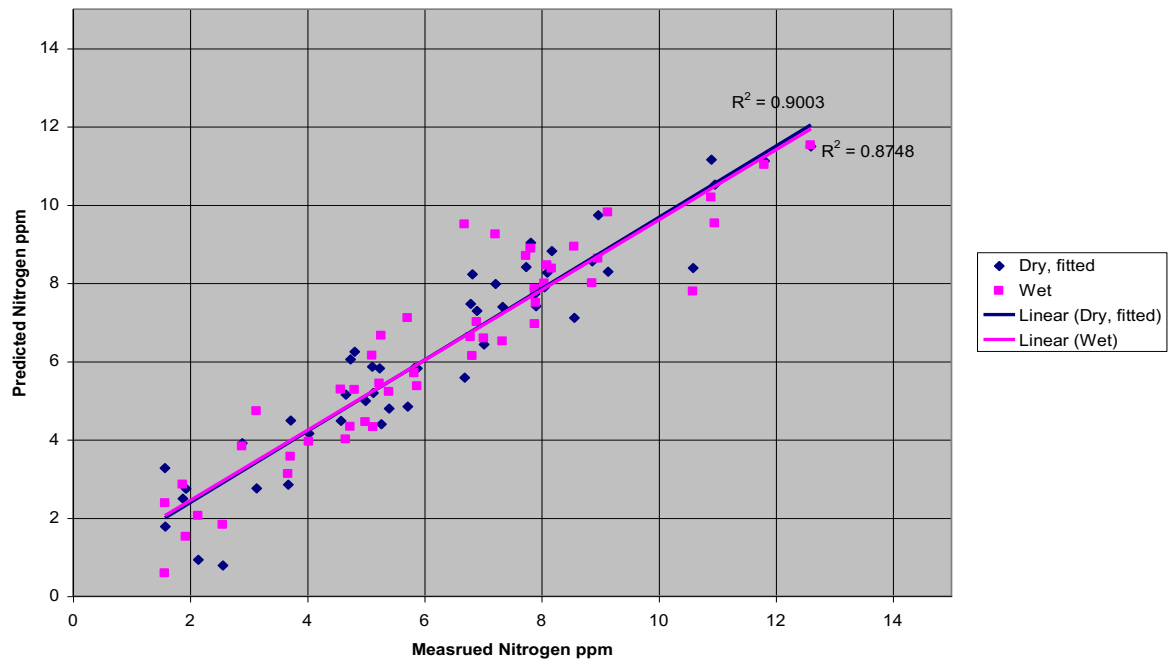
Fig. 6 Predicted Nitrogen Fit

Spectral Fit of Ph versus Chemical Analysis

Fig. 7 Predicted Ph Fit

Organic Material Spectral Fit versus Chemical Analysis

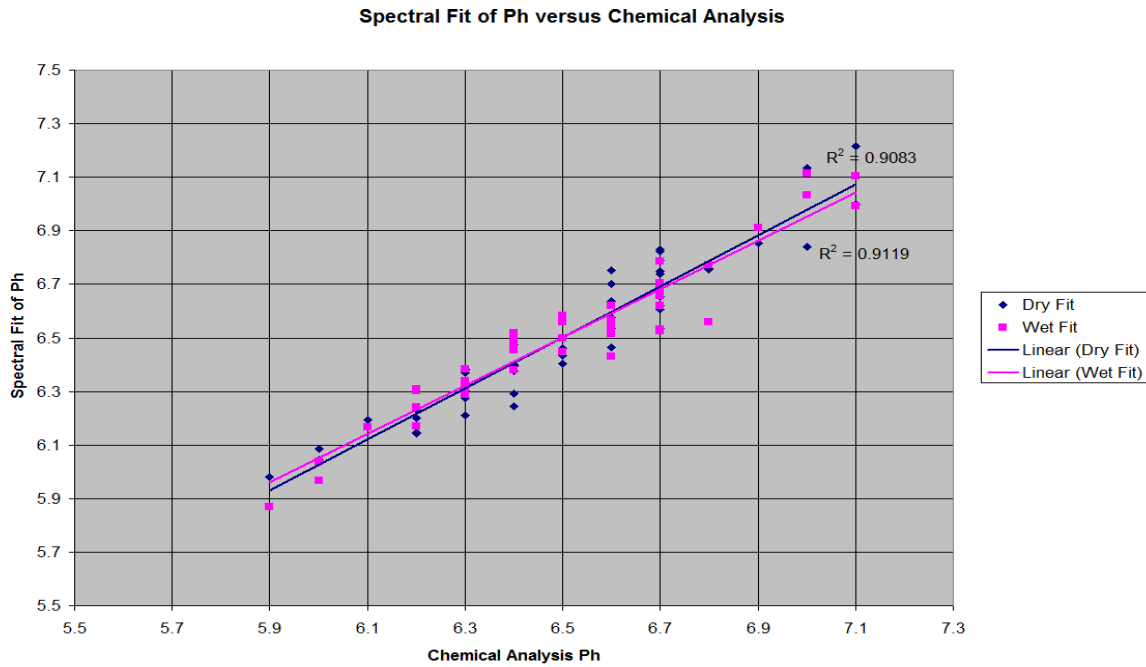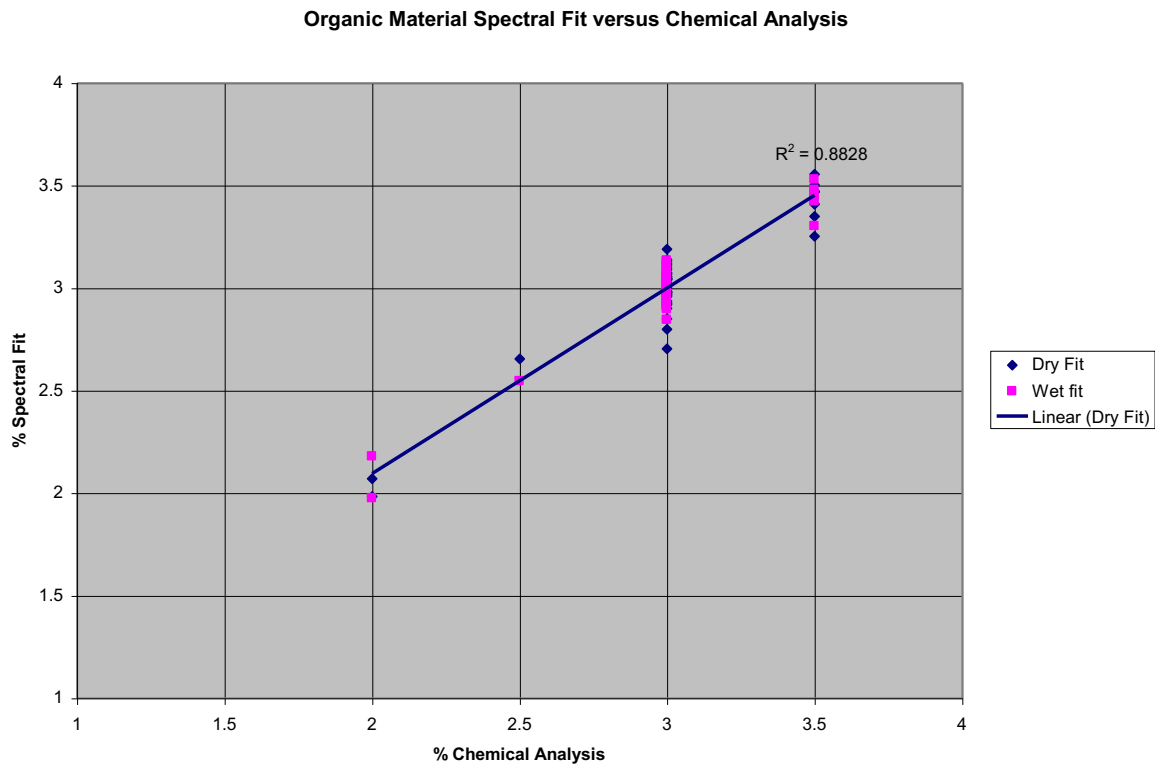**Fig. 8 Predicted Organic Matter Fit**

For all of these fits, N, P, K, Ph, and OM, wet, dry the correlation coefficients range between 0.76 and 0.90, (figure 9) which means that these coefficients do a good job of predicting the measured levels, provided we have fit with the measured levels in the beginning. In other words, if we had an additional 10 samples from the same fields which we hadn't used in the fitting procedure but

measured their reflectance as we did for the fitted samples, we could predict the actual values very well.
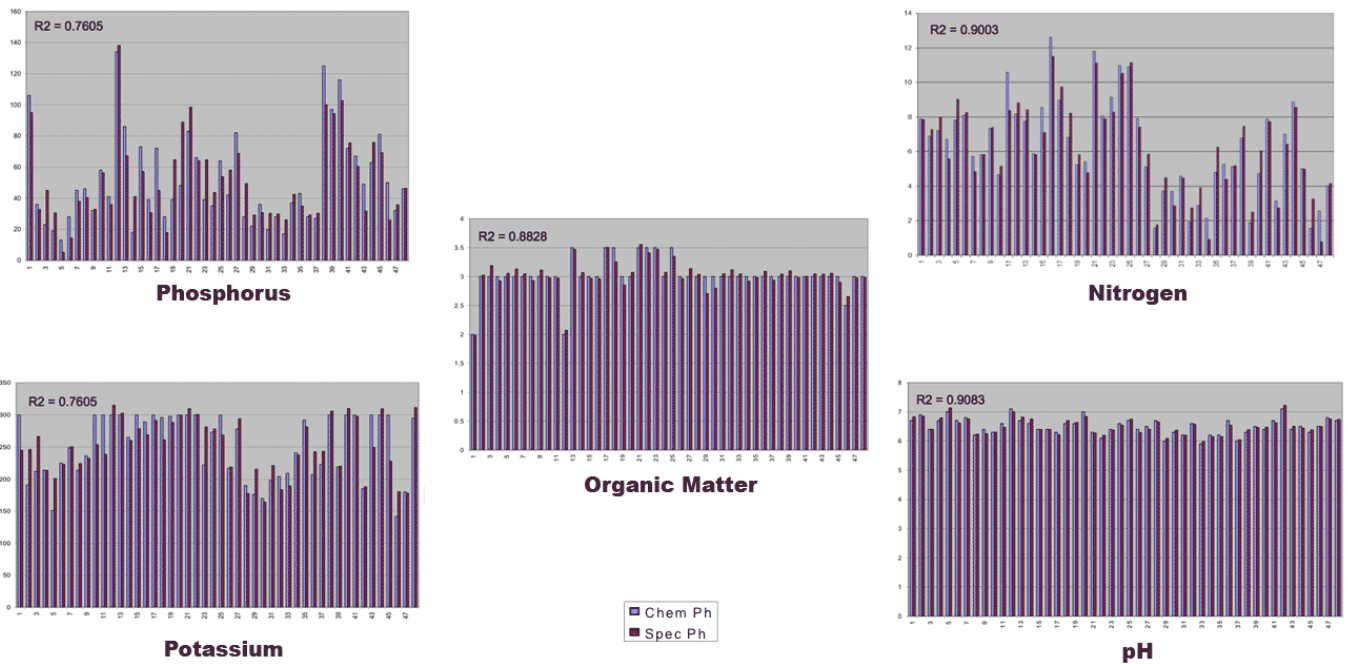

Fig. 9 Correlation Coefficients

Comparison plots of the spatial distribution of the three elements (N, P, K) Ph, and OM generated from the chemical analysis of the 48 soil samples are presented in figure 10. Each page has both the chemical analysis derived plot and the plot generated from the spectral data correlation for comparison. The character and trends of the correlated spectral plots show excellent agreement with the plots coming directly from the chemical analysis.
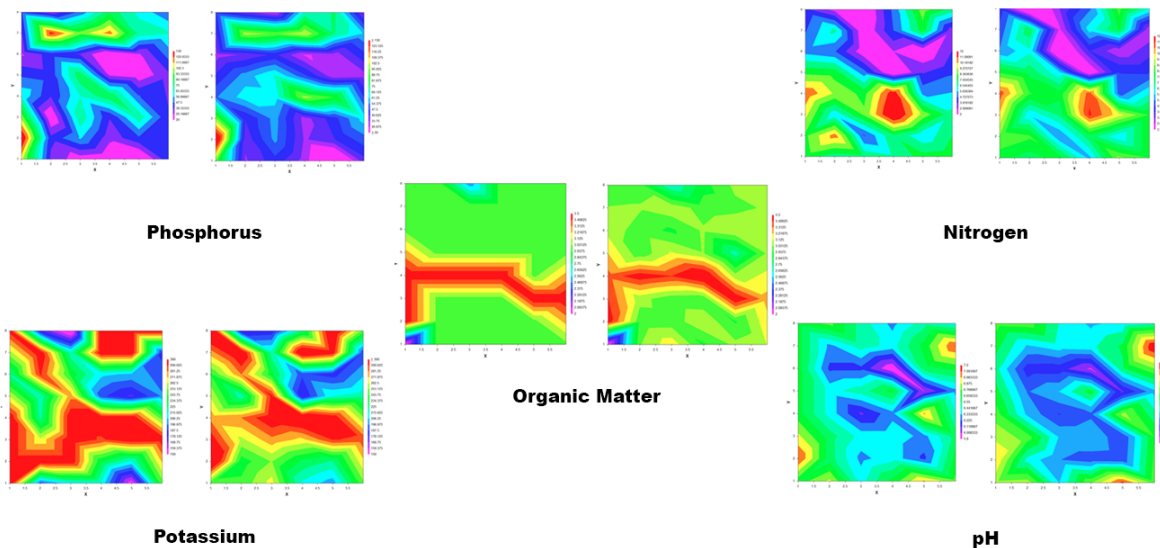

Fig. 10 Comparison Plots

Conclusions:

The fundamental conclusion is that it is possible to measure N, P, K (and probably other desired nutrients/elements) by using a spectrometry genre technology. This was the desired objective of the first milestone and the lab acquisition and subsequent analysis demonstrates the ability to detect the presence and quantify the concentration of NPK in soil. This first test and analysis has demonstrated the ability to identify these elements in a non-contact method, and it now points the way toward the next testing and analysis requirements.

Going forward, from the remote soil sensing data, Persistence Data Mining can develop variable rate nitrogen, phosphorus and potassium application maps. Farmers can achieve fertilizer savings of $15.00 to $40.00 per acre using this system as well as 10 to 15 percent yield increases. The system is also environmentally effective in reducing fertilizer over-application, which leads to runoff and leaching into ground water. By combining an effective suite of well-researched and documented procedures, Persistence Data Mining is developing an industry-leading fertilizer management technology that fully uses variable rate technology's vast potential.

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