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Study on Soil Properties and Spectral Characteristics in Florida

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Abstract. *This study was conducted to find out fundamental relationship between soil properties from 4 representative soil orders in Florida and their spectral characteristics, as a preliminary step to develop a real-time soil property sensor for an effective farm management. Soil samples were obtained at three different depths at 15 sampling locations with 3 replications. Total 540 samples were collected. The samples were measured their reflectance in the range of 400-2500 nm in a laboratory and also were analyzed actual nutrient contents (P, K, Ca, and Mg), pH, and organic matter content. The analysis results showed that the prediction models varied from one soil order to another, and from one depth to another, indicating site-specific calibration is needed. The performance of the prediction models for soil properties using reflectance spectra was generally poor to unacceptable, however there were some reasonably good models, especially for Ca and Mg. The SAS Proc REG, PLS and PCR procedures produced similar models with similar prediction performance.*

Keywords. Soil property, nutrient, sensor, reflectance, spectroscopy, precision agriculture.

Introduction

Precision agriculture has been widely used to improve farm management practices and thus increase profits by increasing yield and reducing management cost. A great deal of improvements in sensor technologies and GPS/GIS enabled growers to use precision technologies, such as yield monitoring and mapping, variable rate application (VRA), and remote sensing.

Among the sensor development efforts, there have been a lot of research activities on developing plant and soil nutrient sensing system, especially for nitrogen (Stone et al. (1996), Sui et al. (1998), Lee at al. (1999), and Lee and Searcy (2000)). However, there were not many investigations reported on sensing P, K, and other micro nutrient elements. Among the nutrient elements, phosphorus has been identified as a pollutant carried into the waterbodies causing eutrophication of lakes, rivers and streams. Excess algal bloom will cause decline in the aesthetic quality of waters along with hypoxia (depletion in dissolved oxygen levels) seriously impacting the aquatic life. Agricultural operations have been determined to be the major contributors of the nutrient loadings into the water bodies. So effective soil testing will determine the actual crop needs of phosphorus nutrient and nutrient management (either through fertilizer or manure) will lead to lesser additions of 'P' and therefore prevent the loss from buildup of 'P' in the soils.

One of the techniques to assess plant and soil nutrient status is near-infrared (NIR) spectroscopy due to its non-destructive method, and labor and cost savings. NIR spectroscopy has been extensively used for many agricultural applications such as water & nutrient stress sensing for agricultural crops (Thomas and Oerther (1972), Al-Abbas et al. (1974), Walberg et al. (1982), Stafford et al. (1989a, b), Blackmer et al. (1994), Yoder and Pettigrew-Crosby (1995), Filella et al. (1995), Blackmer et al. (1996), Ma et al. (1996), Masoni et al. (1996), Sudduth and Hummel (1996), Rigney and Brusewitz (1997), and Bausch et al. (1998)), and weed detection (Wang et al., 2000).

There were several attempts to assess soil fertility among these reports. Otey et al. (1998) designed and evaluated a phosphorous measurement system using water columns and a digital multimeter in a laboratory setting. The system was calibrated with known amount of phosphate concentrations. They reported that concentration increased with depth in the water column and concentration differences between measurement nodes were readily observed at higher concentrations. Ehsani et al. (1999) investigated the possibility of rapidly sensing soil mineral-N content using NIR reflectance. PLS technique was used to analyze the data and reported that 1800-2300 nm range could be used to determine the nitrate content of soil successfully, however calibration equation needed to be obtained from the same location where validation samples were acquired. Ingleby and Crowe (1999) developed linear regressor models to predict soil organic carbon content in 5 Saskatchewan fields and reported that the best model for each field varied in size and reflectance wavelengths, suggesting that site-specific models may be needed. They also reported that alternative model development methods such as PLS, PCR and neural network need to be thoroughly investigated. Shibusawa et al. (1999) developed a real-time portable spectrophotometer for measuring underground soil reflectance in the range of 400-1700 nm. They reported that R^2 value between reflectance spectra and soil properties (moisture, pH, EC, SOM, NO_3-N) varied from 0.19 to 0.87. Thomasson et al. (2000) investigated relationship between soil properties and reflectance spectra using samples obtained in northeastern Mississippi. They reported that only Ca and Mg on one field and clay on the other had multiple regressor model with R^2 values greater that 0.50. They found that 400-800 nm and 950-1500 nm regions had high discriminatory power

The objective of this research was to find fundamental relationship between soil properties from various soil orders in Florida and their spectral characteristics, as a preliminary step to develop a real-time soil property sensor for an effective farm management. Once a real-time soil sensor system is developed, it will greatly decrease the time and drudgery required for collecting soil samples and analyzing them. The sensor system could eventually contribute on increasing yield and profit, as well as reducing environmental concerns greatly.

Materials and methods

Soil sampling

Soil samples were collected from four major soil orders in Florida: Alfisol, Entisol, Histosol, and Ultisol. At each soil sampling location, samples were acquired at three different depths of 0”-6”, 6”-12”, and 12”-18”. Fifteen different sampling locations were selected from each of four major representative Florida soil orders. Three replicated sets of samples were obtained at three different times of the year: February, March, and April 2001. Total 540 samples were collected in this manner.

Analysis of soil properties

All soil samples were analyzed for their pH, Ca, Mg, K, P, and organic matter content at the Analytical Research Laboratory at the University of Florida. Soil samples from Alfisol, Entisol, and Ultisol were mineral soils and were processed by Mehlich-1 soil testing procedure. However, Histosol were mineral soils, and were processed with modified testing procedure. 1.25 g of Histosol samples were weighed (as opposed to 5 g of mineral soil). The data were corrected for the dilutions imposed by adding 20 mL of Mehlich-1 extraction solution. Organic matters were determined by loss on ignition (450° C for 6 hr), as opposed to Walkley-Black dichromate method for the mineral soils.

Reflectance measurement

All soil samples were oven dried at 104° C for 24 hours, ground, and sieved with #30-mesh sieve before measuring their reflectance in order to remove any particle size effect. All soil samples were measured their spectral reflectance with a spectrophotometer (FOSS NIRSystems Inc., Model 6500) from 400 nm to 2498 nm with 2 nm increment in a laboratory setting. One reflectance spectrum contained 1050 measurements at 1050 wavelengths.

Spectral data analysis

The objective of the spectral data analysis was to find wavelengths that would best explain soil properties for different soil orders and at different sampling depths, and to develop prediction models for different soil properties analyzed earlier. In order to build a prediction model for soil properties, regression analysis was conducted using the SAS PROC REG with *Stepwise* selection option. Variables, which were not significant at the 0.15 significance level, were not included in the model. Since there were 3 different sampling depths at 15 different sampling locations per soil order and per month, there were 45 soil samples with same soil order and same sampling depth. Thus, the first 10 samples from each month were chosen to make a 30-sample calibration data set, and the rest of 15 data sets were used as validation data sets.

Prediction models were developed for all soil properties and for all sampling depths, producing total of 72 prediction models (= 4 soil orders x 3 sampling depths x 6 soil properties).

Another common approaches to find important wavelengths are Partial Least Square (PLS) regression, and Principal Component Regression (PCR). PLS regression is related both PCR and multiple linear regression (MLR). PLS attempts to find factors (commonly called latent variables or LVs), which capture variance and achieve correlation (Wise and Gallagher, 2000). The number of latent variables were chosen based on two rules of thumb: (1) only choose additional factors when the predicted residual error sum of squares (PRESS) improves by at least 2%, and (2) choose fewer factors when in doubt (Wise and Gallagher, 2000).

PCR finds factors capturing the greatest variance in the predictor variables and is used properties regressed on the principal component scores of the measured variables. The number of PCs (Principal Components) for building a model was selected based on predicted residual error sum of squares (PRESS). For PLS and PCR procedures, the PLS_Toolbox for use with MATLAB (version 2.1, Eigenvector Research Inc.) was used.

Results and discussion

Table 1 shows results of soil property analysis of the acquired samples. Each number shows average of 15 samples at the same sampling depth and same sampling period. As mentioned before, the Histosol samples were organic soils and thus showed very high concentrations in Ca, Mg, and organic matter than those from other soil orders. Note that organic matter content of Histosol was in the range of 63-74%. The pH of Entisol and Histosol was higher than the pH of Alfisol and Ultisol. P in Alfisol and Histosol showed more variation over sampling period than other soil properties analyzed in the other soil orders.

Figure 1 shows average reflectance curves of different soil orders acquired at the same depth of 0-6” in February 2001. Except Histosol, soil samples from three other soil orders showed similar reflectance characteristics. Histosol showed lower reflectance, since its color was black due to high organic matter content. Figure 2 shows average reflectance curves at different sampling depths for one of the soil orders, Entisol, obtained in February 2001. Reflectance increased as the sampling depth increased. Both figures showed nitrogen absorption band around 510 nm, and water absorption band at 1930 nm. Since two detectors were used in the spectrophotometer, there was a discontinuity at 1100 nm in the reflectance measurement.

Figure 3 shows variation of average reflectance of 15 samples in Entisol obtained at the same depth over different sampling period. The figure shows that there were not much variations of reflectance over time for this soil order. The samples obtained in March had lower reflectance than those from February and April.

Table 1. Results of soil property analysis of soil samples obtained. Each number is an average of 15 samples at the same sampling depth and same sampling period (Ca, Mg, K, and P are in ppm, and Organic matter (OM) is in %).

		Alfisol						Entisol					
Depth		pH	Ca	Mg	K	P	OM	pH	Ca	Mg	K	P	OM
0-6”	Feb	5.4	327.7	51.0	72.4	172.2	2.2	6.0	450.9	63.3	42.8	61.2	1.5
	Mar	5.4	315.7	54.7	60.2	109.4	1.9	6.4	584.6	90.5	51.0	51.8	1.7
	Apr	5.3	362.9	73.4	51.8	122.6	2.2	6.1	583.9	111.3	48.2	51.1	1.4
6-12”	Feb	5.5	342.8	28.0	16.2	118.7	1.1	6.0	266.1	24.0	14.5	63.5	0.6
	Mar	5.5	325.1	31.4	17.8	78.0	1.0	6.3	415.5	41.6	22.8	73.0	0.9
	Apr	5.4	291.2	32.4	21.0	89.4	1.2	6.0	361.9	40.0	22.4	65.2	0.7
12-18”	Feb	5.8	383.3	40.6	24.9	105.0	0.7	6.1	160.3	16.2	10.1	40.8	0.4
	Mar	5.7	260.5	40.7	7.7	54.8	0.4	6.3	252.7	23.8	13.0	56.0	0.7
	Apr	5.5	257.5	37.7	12.6	67.1	0.5	6.0	232.6	24.3	13.0	49.2	0.3
		Histosol						Ultisol					
Depth		pH	Ca	Mg	K	P	OM	pH	Ca	Mg	K	P	OM
0-6”	Feb	6.2	22133	1810	346.6	68.1	63.1	5.3	213.6	22.9	38.9	59.3	1.5
	Mar	6.3	28080	2161	415.5	82.1	68.3	5.4	289.3	38.9	54.7	71.1	1.9
	Apr	6.3	27600	2361	429.8	129.9	72.3	5.3	240.9	37.9	39.5	58.6	1.7
6-12”	Feb	6.2	21407	1333	236.4	158.8	71.0	5.3	99.4	6.5	16.2	66.5	0.6
	Mar	6.3	26493	1690	286.5	52.1	67.6	5.3	135.1	10.8	27.8	84.0	1.1
	Apr	6.4	27340	2044	324.9	94.7	73.7	5.1	80.6	7.6	22.4	69.7	0.9
12-18”	Feb	6.2	19267	1119	202.3	190.5	66.4	5.4	64.9	3.6	10.9	61.9	0.3
	Mar	6.3	25587	1647	262.3	51.1	68.0	5.4	128.9	7.7	19.1	88.5	0.7
	Apr	6.4	26740	1851	290.9	89.7	74.1	5.1	74.9	6.1	17.1	66.8	0.6

Table 2 shows validation results of PLS (partial least square regression) & PCR (principal component regression) procedures with R^2 values higher than 0.50. For P, only one data set (Alfisol, 0-6” sampling depth) produced R^2 values higher than 0.50. The prediction by this model is shown in Figure 4. It was found that it was easier to build prediction models for Ca and Mg, since there were 5 models for Ca and 7 models for Mg produced for the given data sets. The prediction models for Mg from Histosol at 6-12” and organic matter from Ultisol at 12-18” used only 1 latent variable for PLS and 1 principal component for PCR procedures. There were no prediction models produced for K by both PLS and PCR procedures. When the performance of PLS and PCR procedures were compared for the same validation data set, PLS regression produced generally better prediction results (higher R^2 values) than PCR.

Table 3 shows results of multiple linear regression of soil properties of both calibration and validation data sets, conducted by the SAS PROC REG. This procedure produced generally similar results to those by PLS and PCR procedures (Table 2). The prediction models were bold-faced in the table if their prediction performance determined by R^2 values was higher than 0.50. Interestingly enough, all the bold-faced models were also chosen by PLS and PCR procedures (Table 2). The REG procedure produced one model for K element (Entisol at 6-12” sampling depth), with R^2 values higher than 0.50, however no model for P was produced by this procedure.

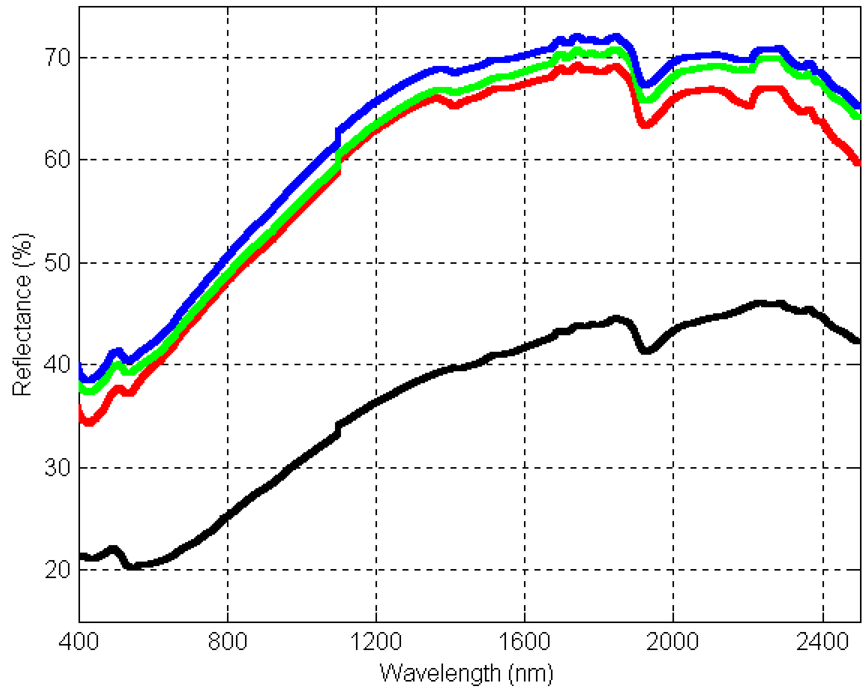

Figure 1. Reflectance curves of different soil orders acquired at the depth of 0-6” in February 2001: Alfisol (red), Entisol (green), Histosol (black), and Ultisol (blue).

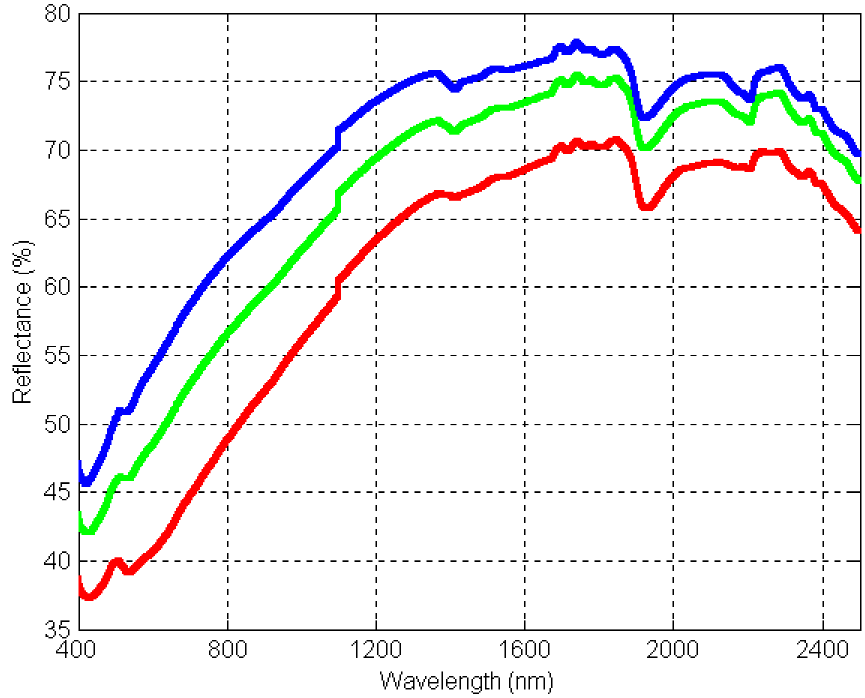

Figure 2. Reflectance curves of Entisol at different depths acquired in February 2001: 0-6” (red), 6-12” (green), and 12-18” (blue).

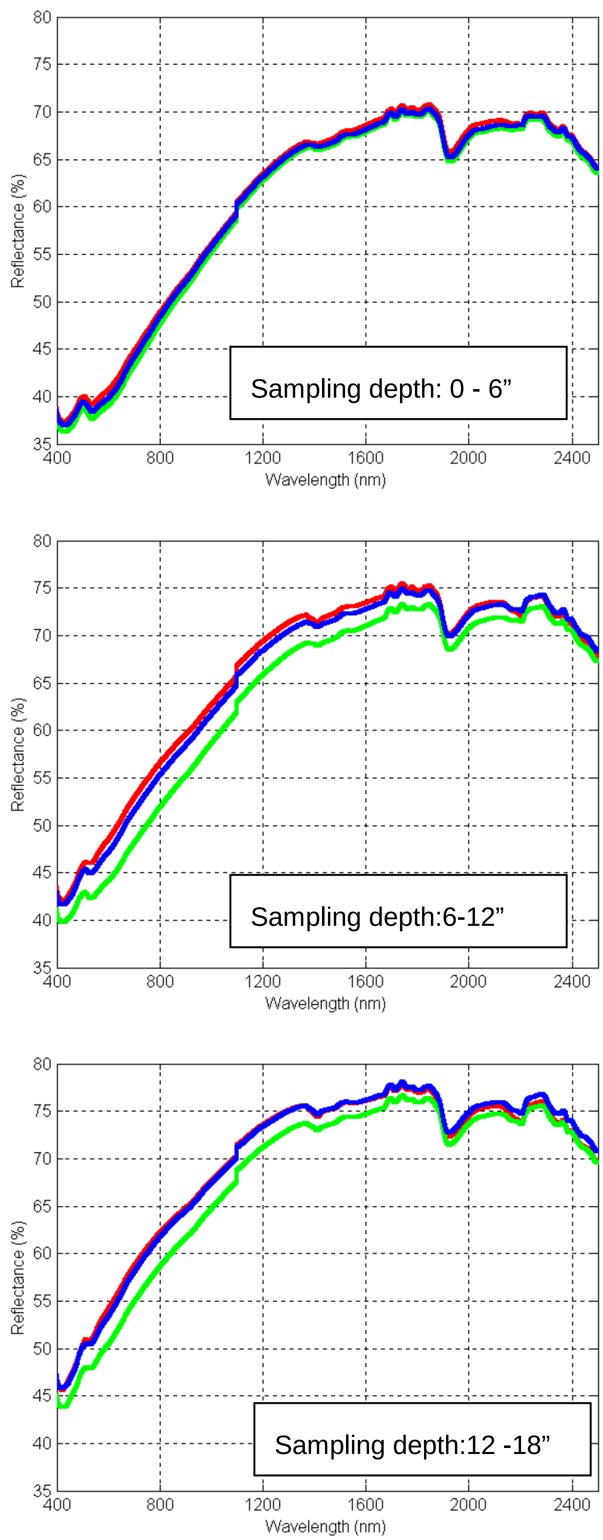

Figure 3. Variation of reflectance of the Entisol samples obtained at the same sampling depth over 3 month periods: February (red), March (green), and April (blue).

Table 2. Validation results of PLS and PCR regression models with R^2 higher than 0.50. #LV and #PC are number of latent variables and principal components in PLS and PCR prediction model, respectively. PRESS is predicted residual error sum of squares.

Soil order	Depth	Soil property	PLS			PCR		
			#LV	PRESS	R^2	#PC	PRESS	R^2
Alfisol	0-6”	P	6	19.0	0.664	8	19.2	0.656
		OM	3	0.33	0.500	5	0.32	0.521
	6-12”	pH	6	0.324	0.613	7	0.35	0.504
		Ca	9	92.5	0.632	6	117.7	0.676
	12-18”	None	-	-	-	-	-	-
Entisol	0-6”	Ca	7	109.0	0.521	6	109.1	0.446
		Mg	6	23.0	0.613	7	24.9	0.539
	6-12”	Ca	5	52.4	0.717	6	50.7	0.730
		Mg	3	9.94	0.615	3	10.2	0.580
	12-18”	Mg	6	5.11	0.576	6	5.29	0.511
Histosol	0-6”	Ca	6	2034.8	0.657	6	2130.8	0.625
		Mg	5	249.7	0.459	7	177.1	0.624
	6-12”	Mg	1	389.2	0.765	1	391.1	0.778
	12-18”	None	-	-	-	-	-	-
Ultisol	0-6”	Mg	6	11.8	0.546	7	11.9	0.538
	6-12”	OM	1	0.235	0.594	1	0.235	0.593
	12-18”	Ca	6	46.4	0.718	7	55.7	0.458
		Mg	7	3.43	0.650	6	4.92	0.328
		OM	1	0.180	0.728	1	0.180	0.728

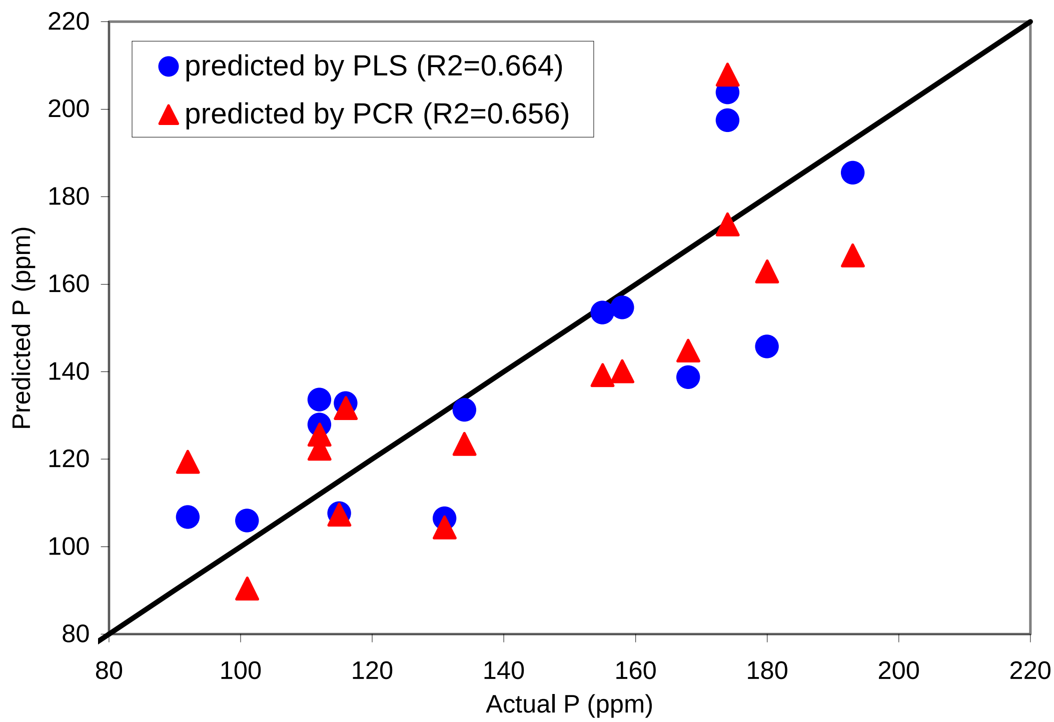

Figure 4. P-prediction of Alfisol at 0-6” by PLS and PCR procedures.

Table 3. Result of multiple linear regression by the SAS PROC REG (continued to next page).

Soil order	Sampling depth	Soil property	Wavelength selected (nm)	Calibration set		Validation set	
				RMSE	R^2	RMSE	R^2
Alfisol	0-6”	pH	400, 498, 504, 572	0.23	0.524	0.208	0.014
		Ca	846, 850, 870, 1904, 1926, 1948, 1956, 2142	41.9	0.913	77.1	0.483
		Mg	412, 470, 2212, 2470, 2472, 2480	11.8	0.811	23.4	0.059
		K	-	-	-	-	-
		P	404, 494, 546, 1382, 1384, 2496	13.9	0.868	25.2	0.440
		OM	406, 492, 500, 506, 522, 544	0.25	0.760	0.43	0.104
	6-12”	pH	1506, 1512, 1722, 1760, 1762, 1782	0.16	0.743	0.20	0.246
		Ca	**1916, 2166, 2302**	**55.3**	**0.709**	**76.9**	**0.640**
		Mg	1948, 2224, 2308	9.05	0.293	14.1	0.133
		K	492, 2232	7.77	0.332	14.3	0.241
		P	784, 916, 932, 1412, 1414, 2232,	15.6	0.690	24.2	0.148
		OM	1432	0.22	0.184	0.45	0.116
	12-18”	pH	-	-	-	-	-
		Ca	522, 530, 550	49.8	0.371	366.9	0.070
		Mg	-	-	-	-	-
		K	-	-	-	-	-
		P	446, 452, 1926, 2204, 2464, 2470	10.9	0.809	63.4	0.042
		OM	980, 1110, 1112	0.16	0.491	0.58	0.030
Entisol	0-6”	pH	414, 448, 462, 464, 1630, 1632	0.18	0.680	0.16	0.217
		Ca	**518, 522, 534, 2360, 2444, 2498**	**51.6**	**0.942**	**43.3**	**0.891**
		Mg	**422, 1832, 1862, 1864, 2048, 2128**	**10.9**	**0.881**	**25.9**	**0.513**
		K	**2462**	**11.4**	**0.370**	**10.0**	**0.509**
		P	1088, 1098, 1114, 1162, 1188, 1192	11.3	0.774	10.1	0.010
		OM	402	0.51	0.105	0.38	0.084
	6-12”	pH	402, 436, 460, 490, 492, 510, 512, 538	0.15	0.753	0.21	0.400
		Ca	432, 492, 506	84.7	0.569	77.3	0.435
		Mg	**462, 1836, 1842, 1894, 1898, 1940, 1946, 2262**	**5.48**	**0.863**	**8.1**	**0.693**
		K	-	-	-	-	-
		P	-	-	-	-	-
		OM	514, 524, 556, 562	0.15	0.686	0.16	0.333
	12-18”	pH	420, 424, 450, 522, 574, 588, 592	0.13	0.782	0.23	0.020
		Ca	522, 526, 530, 558, 578, 596	41.1	0.750	61.9	0.007
		Mg	**1930, 2140**	**5.81**	**0.504**	**4.8**	**0.581**
		K	2442, 2452	3.16	0.431	7.2	0.160
		P	408, 420, 626	10.9	0.459	10.5	0.176
		OM	434, 470	0.20	0.599	0.24	0.110

Table 3 (continued from previous page). Result of multiple linear regression by the SAS PROC REG.

Soil order	Depth	Soil property	Wavelength selected (nm)	Calibration set		Validation set	
				RMSE	R^2	RMSE	R^2
Histosol	0-6”	pH	548, 580, 592	0.11	0.306	0.08	0.300
		Ca	**442, 478, 490, 494, 574, 586**	**620.5**	**0.961**	**1572.3**	**0.713**
		Mg	**400, 686**	**132.9**	**0.760**	**180.2**	**0.625**
		K	410, 418, 428, 488	43.5	0.642	62.8	0.024
		P	536, 540, 614, 684, 2282, 2284	9.14	0.916	22.9	0.436
		OM	400, 402, 1506	3.75	0.668	4.48	0.018
	6-12”	pH	404, 554, 560	0.11	0.519	0.11	0.163
		Ca	400, 436, 450, 558, 624, 928	1140.6	0.856	2721.7	0.413
		Mg	-	-	-	-	-
		K	400, 726, 1936	35.6	0.479	61.1	0.204
		P	400, 434, 530	13.3	0.793	459.7	0.062
		OM	1912, 1934	3.39	0.380		
	12-18”	pH	400, 512, 518, 522, 546, 622	0.09	0.730	0.14	0.040
		Ca	924, 1010	3430.2	0.354	2972.7	0.234
		Mg	538, 910, 924, 1008, 1012, 1102, 2494, 2496	174.9	0.858	287.0	0.455
		K	400, 402, 1098, 1118, 1120	34.3	0.569	45.2	0.270
		P	-	-	-	-	-
		OM	-	-	-	-	-
Ultisol	0-6”	pH	1910, 1972, 2136	0.20	0.530	0.16	0.424
		Ca	1944, 1948, 1984, 2000, 2018, 2308	39.9	0.826	86.9	0.266
		Mg	**648, 1942, 2146**	**9.42**	**0.532**	**12.9**	**0.512**
		K	446	11.2	0.163	17.4	0.032
		P	-	-	-	-	-
		OM	2288, 2458, 2498	0.48	0.320	0.45	0.116
	6-12”	pH	-	-	-	-	-
		Ca	420, 490	3.72	0.412	80.9	0.010
		Mg	410, 418, 420, 510, 528	2.58	0.750	6.76	0.020
		K	2284, 2288, 2412, 2428, 2476, 2482	4.11	0.739	12.2	0.087
		P	1888, 2006, 2162, 2226, 2318	12.9	0.602	23.9	0.132
		OM	**756**	**0.24**	**0.395**	**0.22**	**0.642**
	12-18”	pH	-	-	-	-	-
		Ca	**1392, 1394, 1910, 1974, 2194, 2212**	**30.4**	**0.879**	**49.3**	**0.613**
		Mg	1908, 2178, 2306	2.74	0.628	4.79	0.389
		K	2210, 2492, 2494	5.79	0.382	10.2	0.051
		P	2480, 2498	26.4	0.325	27.4	0.037
		OM	**600**	**0.19**	**0.575**	**0.16**	**0.747**

Conclusion

This study was conducted to find fundamental relationship between soil properties from various soil orders in Florida and their spectral characteristics, as a preliminary step to develop a real-time soil property sensor for an effective farm management. The major findings from this research were:

- Soil samples obtained for this research produced better prediction models with higher R^2 values for Ca and Mg than those for other soil properties.
- Three different procedures (PLS, PCR and REG) were used to build soil property prediction models using reflectance measurements and they produced prediction models for similar soil properties with similar prediction capability.
- The prediction models varied from one soil order to another, and from one sampling depth to another, which would require site-specific calibration in future implementation.

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