DETECTION OF FERTILIZER QUANTITY IN SOIL USING HYPERSPECTRAL DATA

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ABSTRACT

Improvement in the crop yield in sustainable fashion requires application of the agro-chemicals in right quantity, right place, and at right time. Hyperspectral detection of agro-chemicals provides an opportunity to develop innovative methods in this regard. The present study reports efforts taken in the same direction. We focus on fertilizer application and attempt to analyze the spectral signature of soil and fertilizer mixture. Further, we develop a correlation between the diagnostic depths and concertation of the fertilizer in the soil using multiple and simple regression.

Index Terms— Hyperspectral data, NPK fertilizers, Precision agriculture, Multiple regression, SVM

1. INTRODUCTION

Providing food security to the population of nine billion people by 2050 is a challenging task. Though the global demand would be achieved at the current growth rate at the global scale, meeting the projected demand at the regional/country scale is a challenging task still [1]. India needs 340 million tons of food grain to meet its demand [2]. Increase in yield of a given area under a crop is expected to be one of the most important factor required to meet this demand [1]. The use of fertilizers in India has been increased by 170 times in last 50 years (1960 – 2001-02, 0.55 kg/ha to 90.12 kg/ha) [2]. Use of fertilizers is expected to grow further because of future requirements.

The fertilizers may be required to fuel food production, but the excess of it is harmful to sustainable development. Food and Agricultural Organization (FAO) considers agro-chemicals such as pesticides and fertilizers as important hazards [3]. Excess of nutrients are carried away by agricultural runoff into water streams and it leads to eutrophication of natural ecosystems. Ground water is also affected by excess nitrates and in some cases may render water unfit for drinking [4]. Cadmium, one of the constituents of phosphorous fertilizers, is harmful to human health. Cadmium is non-nutrient constituent and is readily absorbed by plants as compared to other trance minerals. Cadmium is known to affect renal, pulmonary and cardiovascular health adversely [5], [6].

Because of these conflicting goals, application of fertilizers in a precise manner is important. Efficiency of nutrients can be improved by improving timing and placement of fertilizers [1]. There are limited efforts to measure the fertilizers in soil using imaging spectroscopy.

One of the early notable study by Ben-Dor and Banin [7] used high spectral resolution measurements within the 1000 nm to 2500 nm range to correlate it with physical and a few chemical properties of the soil. 3113 measurements were reduced to 25, 30, 60, and 310 measurements using simple average and these readings were correlated with soil properties using multiple regression. Soil properties considered were clay content, specific surface area, cation exchange capacity, hygroscopic moisture, carbonate content, and organic matter content. Thirty bands found moderate relation with organic matter content. The wavelengths found optimal for the organic content prediction were 2338.3 nm, 2016.5 nm, 1941.0 nm, 1584.9 nm, 1412.2 nm, and 1042.9 nm. The study did not consider the agricultural chemicals such as fertilizers and pesticides. In similar such study, Ben-dor and Banin [8] further studied the soil properties and correlation between thematic mapper (TM) bands. Boggs *et al*. [9] studied relation between hyperspectral signatures collected over 400 nm to 1000 nm with four nm spectral resolution and cotton yield. The relation between chlorophyll and soil nitrogen was established and it was suggested that the chlorophyll content could be used to indicate deficiency of nitrogen. Thus, the indirect relation between hyperspectral signature and soil nitrogen was established. Study found that the 807.6 nm wavelength as a significant wavelength for cotton leaf chlorophyll. This study as well did not attempt establishing spectral characteristics of agricultural chemicals such as fertilizers and pesticides. Ge *et al*. [10] provided short and concise review of remote sensing of soil properties. Most of the earlier research focus on physical and biochemical properties of soil. There is limited study on the measurements of agricultural chemicals with the perspective of precision application.

Objective of this research is to study the hyperspectral signatures of soil-fertilizer mixtures and the variation in the signatures for different proportion of the fertilizer, if any. We attempted to find the diagnostic depth of Suphala [11], one of the most common fertilizers used in India, and tried to correlate it with the proportion of the fertilizer in the soil.

Some of the specific research questions that we investigated were: Do the fertilizers have specific diagnostic depth? Does the signature vary with the concertation of fertilizer in soil-fertilizer mixture? Is the diagnostic absorption good enough to develop quantification question?

We created soil-fertilizer mixtures with different concertation of the fertilizer. We recorded the signatures of the mixtures. We then removed the continuum from the spectral signature and calculated the diagnostic depths at specific wavelengths identified using manual analysis. Then we used multiple regression to correlate the concertation with depth. Further, we identified the category of mixtures using classifier such as Support Vector Machine (SVM) [12].

2. MATERIALS AND METHODS

2.1. Soil-fertilizer mixture and hyperspectral measurements

We created different mixtures of soil and the fertilizer in different proportions by volume. The ratios of soil to fertilizers were 3:3, 3:2.5, 3:2, 3:1.5, and 3:1. The soil and the fertilizer were mixed adequately to avoid concentration of fertilizers on the surface of the soil. The soil depth of 10 cm was maintained in the trays, which is equivalent to the fertilizer mixing depth in the field application. The fertilizer quantity used was more than the recommended by the guidelines. This was required to establish the effects of fertilizer on soil signature. The fertilizer used to create the mixtures was chosen as the most common Nitrogen-Phosphorus-Potash (NPK) fertilizers used in India – Suphala 15:15:15 [11]. Suphala contains nitrogen, phosphorus and potash in equal proportion that is 15%. We used two soil samples: Sample 1: was most representative farm soil. The inherent phosphorus and potash concentration was 935 ppm and 511 ppm respectively. Sample 2 was sandy clay with Phosphorus and potash concentration 1000 ppm and 355 ppm respectively.

We used ASD FieldSpec 3 spectrometer for measuring spectral signatures of the mixtures. The spectrometer covers the wavelength range from ~350 nm to ~2500 nm. The measurements were recorded within two hours of local noon. Hundred readings for each mixture was taken by targeting different locations within the each tray. The pistol grip of the instrument was kept at ~1 m away from the body to avoid scattering from clothing, if any. Readings were taken in the direction perpendicular to azimuth [13]. Reference (white plate) reflectance was measured at the beginning of every new set of the measurements, or on minor changes in the atmospheric conditions. The measurements were taken on cloud free days. Temperature and relative humidity of 37.2^{o} C, and 60 % was observed during the data collection. Over all the data set contains 1400 number of signatures along with their concentration.

2.2. Diagnostic depth calculation

The diagnostic depth calculation is performed in three stages. In the first stage, visual analysis determines the range within which there is possibility of finding minimum reflectance values than normally observed, for example, 1450 nm – 1780 nm (Fig. 1). The second automated process then takes these starting and ending wavelengths as input and calculates local minima within that zone. Next, a particular wavelength is chosen manually (from the local minima) to calculate the diagnostic depth. In the third stage, automated process takes starting, ending, and target wavelength as input and calculates the depth at the target wavelength.

Instead of fitting a continuum over a complete spectral curve, we define a continuum over predefined points of interest on a spectral curve. These ends represent the reflectance values at starting and ending wavelength range within which we are interested in calculating diagnostic depth. We fitted 2nd degree polynomial between the two extreme points. Once the 2nd degree polynomial was fitted, the depths at predetermined wavelengths were calculated using straight-line distance between the point on the continuum and the point on the reflectance curve.

2.3 Quantification

We developed a relation between a few selected wavelengths and the fertilizer concentration in the soil using multiple and simple regression. Diagnostic depth at predefined wavelengths is treated as independent variables and fertilizer concentration is treated as a dependent variable.

In addition to the multiple regression, we performed classification of the mixture signatures using SVM. We used reflectance values of all the noise free bands (1816) as features. We used Principle Component Analysis (PCA) to reduce the features to 45 from initial set of 1816. 45 PCA features represent 99% variation in the data.

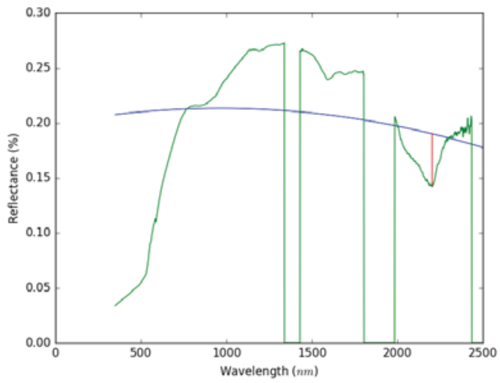

Figure 1. Diagnostic depth calculation (red line indicates the diagnostic depth)

We considered seven classes for the exercise: class c1 is soil, and c7 is fertilizer, remaining classes c2-c6 indicate increasing proportions of fertilizer. We further compared the classification results using PCA features and diagnostic depth features. The reflectance values from significant wavelengths were chosen as features. We used fivefold cross validation for accuracy assessment.

3. RESULTS AND DISCUSSION

3.1. Diagnostic absorption

Figure 2 shows the average spectral signatures of the soil and fertilizer mixtures with fertilizer in different proportions. Water absorption bands are removed from the plot and are not considered for analysis. The overall average brightness of the soil signature is increased because of addition of white Suphala granulates. Manual analysis of the signatures reveals three different zones of soil-fertilizer mixture spectrum that have significant deviation from the soil spectrum. These three zones correspond to wavelengths 350 nm – 750 nm, 1450 nm – 1780 nm, and 2000 nm – 2300 nm. Out of these zones, the second zone and third zone show dominant absorption. The absorption depth is proportional to the concentration of fertilizer (Fig. 2). It is to be noted though that the absorption is a result of nitrogen, phosphorus, and potash together. In the present scope, the diagnostic absorption because of individual nutrient is not considered.

The first zone absorption is meek and is evident only at very high concertation of fertilizer in the mixture. The specific absorption occurred at 1594-1680 nm for the second zone, and at 2200 nm for the third zone. The behavior is very similar for both the soil samples: the soil texture and the inherent constituents of each sample do not affect the absorption wavelengths much.

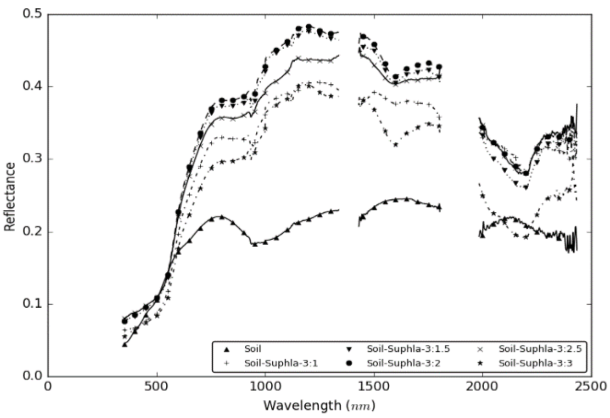

Figure 2. Spectral signatures of soil-fertilizer mixtures in different proportion

3.2. Results of multiple regression

Table 1 summarizes the coefficients (C1 to C3) of dependent variables *i.e.* diagnostic depths for a fertilizer concentration. Multiple experiments were performed on both the soil samples and on the combined dataset. Both the soil samples show similar trends. R^2 values of multiple regression for both the soil samples were 0.95 and 1. Combined dataset provides good degree of correlation as well (Table 1-3).

The single most significant wavelength out of the three is 1680 nm, based on the degree of correlation. The wavelength of 525 nm provides poor degree of correlation individually. However, when it is paired with 1680 nm wavelength features, the degree of correlation improves considerably (Table 1-3). Overall, all the observed diagnostic wavelengths provide a good degree of correlation and can be used for predicting concentration of the fertilizer in the soil. The standard deviation (SD) of predicted values are shown in the last column of the tables 1-3. The equations were used to predict concentration of fertilizers for ~20% of the samples.

Table 1. Relation between diagnostic absorption and fertilizer concentration

	Intercept	C1 (525)	C2 (1680)	C3 (2200)	R^2	SD
Multiple	-0.04	1.10	24.34	9.13	0.81	0.45
Simple	-0.58	2.93			0.07	0.09
Simple	0.20		34.03		0.81	0.38
Simple	-0.39			28.48	0.76	0.74
Multiple	0.16	1.91	33.38		0.82	0.38
Multiple	-0.08		21.31	12.47	0.82	0.49
Multiple	-0.39	-0.51		28.98	0.73	0.75

Table 2. Relation between diagnostic absorption and fertilizer concentration for sample 1

	Intercept	C1 (525)	C2 (1680)	C3 (2200)	R^2	SD
Multiple	-1.65	61.79	121.63	-60.22	0.95	1.67
Simple	-2.00	53.79			0.18	0.87
Simple	0.09		45.59		0.66	0.75
Simple	-0.45			29.52	0.75	0.43
Multiple	-1.23	28.27	39.45		0.83	0.60
Multiple	-0.12		29.19	11.04	0.66	0.51
Multiple	-1.12	16.05		26.22	0.67	0.69

Table 3. Relation between diagnostic absorption and fertilizer concentration for sample 2

	Intercept	C1 (525)	C2 (1680)	C3 (2200)	R^2	SD
Multiple	0.36	11.13	21.62	-3.50	1.00	0.44
Simple	0.43	22.72			0.85	0.74
Simple	0.22		30.62		0.92	0.38
Simple	-0.36			28.30	0.72	0.76
Multiple	0.28	10.62	19.03		0.99	0.46
Multiple	0.19		29.27	1.50	0.88	0.39
Multiple	0.09	15.65		11.43	0.86	0.71

3.3. Results of classification

Table 4-7 provide precision and recall values for the SVM classifier and different features. Both the soil samples show very similar trends in classification as well. PCA features provide the best features among the different features considered. The advantage of dimensionality reduction is evident from the results using PCA features. It is to be noted though that there were 45 features still. Though the diagnostic depths provide very good correlation with the fertilizer concentration, the reflectance values of the same wavelengths are not useful for classification. As only three features are used in this case, the accuracy is dropped by substantial margin. The probable reason might be that the advantages provided by large number of bands (features) is lost because of extreme dimensionality reduction [14], [15].

Table 4. Classification Precision (%) for different features for sample 1

	Class 1	2	3	4	5	6	7	OA
All features	100	89	68	56	50	94	100	78
PCA	100	100	83	92	75	95	100	92
Diagnostic Wavelengths	95	70	44	22	17	33	25	44

Table 5. Classification Recall (%) for different features for sample 1

	Class 1	2	3	4	5	6	7	OA
All features	100	100	95	60	71	68	56	78
PCA	100	100	95	80	88	86	93	92
Diagnostic Wavelengths	76	100	40	27	24	41	11	44

Table 6. Classification Precision (%) for different features for sample 2

	Class 1	2	3	4	5	6	7	OA
All features	100	100	52	65	53	44	81	71
PCA	100	95	65	94	77	90	95	87
Diagnostic Wavelengths	91	84	33	67	25	28	39	52

Table 7. Classification Recall (%) for different features for sample 2

	Class 1	2	3	4	5	6	7	OA
All features	100	95	93	59	36	47	68	71
PCA	100	95	100	68	91	53	100	87
Diagnostic Wavelengths	84	100	73	9	5	41	58	52

4. CONCLUSION

We observed diagnostic absorption at a few specific wavelengths because of NPK fertilizer Suphala mixed in soil. We have developed a quantification equation between the diagnostic depths and the fertilizer concentration in soil. It would be challenging task to verify whether the developed equations remain valid for low to very low concentrations of fertilizers. We plan to extend these experiments with more number of soil samples and a few additional fertilizers.

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