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Hyper spectral Analysis of Soil Iron Oxide using Fieldspec4 Spectroradiometer

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Abstract— The main goal of this study is to discover the iron oxide content in soil using Vis-NIR spectroscopy with the help of ASD FieldSpec4 instrument. Estimation of iron Oxide content can be utilized as an indicator for soil fertility. The instrument ASD FieldSpec4 Spectroradiometer is utilized for capturing spectral signature of gathered soil samples from various areas in Jalna district of Maharashtra state in India. In the Vis-NIR wavelength range we utilized Partial Least Squares Regression (PLSR) method to estimate the iron oxide content present in the samples of soil. Also few pre-processing methods were applied such as savitzky golay and first derivative preprocessing. The outcomes were assessed by root mean square error (RMSE) and coefficients of determination (R^2). The observations with the help of PLSR models with the first derivative pre-processing was (RMSE =0.008711, R^2 =0.91 for calibration and RMSE= 0.001624, R^2=0.92 for validation) and with savitzky golay pre-processing was (RMSE =0.004415, R^2 =0.87 for calibration and RMSE=0.004209, R^2=0.89 for validation). It is inferred that, 444nm, 480nm, 529nm, 680nm, 880nm and 920nm wavelength bands are sensitive to soil iron oxide. Taking everything into account, concentrations of iron oxide in soils could be surveyed by soil spectra; therefore, spectral reflectance would be an elective tool for monitoring soil metals.

Keywords— Iron oxide content, ASD fieldspec4 spectroradiometer, PLSR, Vis-NIR.

I. INTRODUCTION

Good information of soil nutrients is essential in farming for the development of crops. As indicated by the many authors attributes of soil can be chemical, biological, mineralogical and physical [1]. Soil quality assessment helps basic leadership for a scope of worldwide issues, for example, food production and precision agriculture [2]. The monitoring and assurance of soil properties give a better understanding of the physical and chemical processes in soil environments [3]. Reflectance spectroscopy can quantitatively estimate these soil properties more effectively and quickly contrasted with customary lab investigation. Visible-near infrared (Vis-NIR) spectroscopic data in the 350-2500 nm range has been generally used to analyze soils because it effectively associates the chemical components with their particular absorption spectral features [4]. The investigation of iron oxide is of great pedological interest in light of the fact that the iron oxide presents in the soil mirrors the time period and power regarding to pedogenesis [5]. It makes them a proper pedogenic indicator because of their worldwide presence in soils [6]. Main fundamental trait of soil is color and principle pigmenting specialist in soil is iron oxide. As a piece of various investigations to overview the mineralogy of iron oxide to depict soil progression, colors of soil have been used by many authors [7]. And also Iron oxides are critical soil pigments which influence soil supplement take-up by plants [8]. Soil coloring is an essential estimation made in the characterization of soils and Spectral reflectance is a quantitative method of measuring soil color. As spectral reflectance of soils has a direct relationship with soil color, iron oxide influences reflectance of soil [9].

To narrate spectra's with estimated features of substances, different strategies have been utilized for ex. PLSR, Stepwise Multiple Linear Regression, and PCA are the most utilized strategies for calibration. But amongst them PLSR is considered as a robust method which deals with both dependent and independent variable to anticipate characteristic of soil [10].

Mainly, Reflectance spectroscopy gives the potential to evaluate iron oxide content in soil and in this manner it can be utilized as a more effective system to decide soil data when fast, convenient investigations are required.

II. RELATED WORK

Changkun Wang et. al. analyzed the ability of Vis-NIR reflectance spectroscopy for deciding Rare Earth Elements i.e. REE present in the soil. To catch the spectral signature of soil sample, they used Field Spec 4 spectroradiometer.

Furthermore for the estimation of rare earth elements, they used Inductively Coupled Plasma-Emission Spectrometry (ICP-ES) and Mass Spectrometry (ICP-MS). They used PLSR to adjust the spectral signature of soil and evaluated reference estimations of REE by ICP-MS. [11].

C. Canasveras Sanchez et.al. Studied the helpfulness of reflectance spectroscopy for the assurance of a few features of Mediterranean soils, specially focus on iron oxide, carbonate accumulation in soil. They used partial least squares regression for further investigation about Fe chlorosis [12].

Snehal N. Kulkarni et.al. Utilize ASD Field spec4 to evaluate specific content present in farm soil using spectral signature of soil samples [13].

Ji Wenjun et. al. has done investigation for paddy soil features by utilizing lab based VNIR spectroscopy and on field VNIR spectroscopy. They found that for gaining data of paddy soils; on field estimations utilizing VNIR spectroscopy give a productive method. [14].

Ashwini Dilip Padmanabhi, Dr. R. R. Deshmukh Ashwini used ASD fieldspec4 instrument for estimation of nitrogen content from collected soil samples along with PLSR method. [15].

III. METHODOLOGY

A. Study Area:

We have selected Jalna region which is located in Maharashtra as our study area. The Soil Samples were collected from different agricultural lands in Jalna District of Maharashtra state in India.

B. Gathering of Soil samples:

Using 30 soil samples from different regions we made database of soil. Soil samples were collected from the top soil (0-20 cm depth from land surface) and stored in an air-tight plastic bag. The soil samples were air dried for a few days under ordinary room temperature. Little bits of stones and plant parts in the soil samples were evacuated by hand picking before analysis. Then the soil samples were sieved through 2mm sieve and taken for estimations to the laboratory.

C. Spectral Measurements using FieldSpec4:

The FieldSpec4 Spectroradiometer was used for estimations of soil samples. With the help of ASD Field Spec 4 spectroradiometer at Visible-Near Infrared wavelengths extending from 350nm to 2500nm, spectral signature of each and every soil sample were captured. To limit the impact of outside light, the spectra scanning procedure was completed in a dark room. The sampling interval and spectral resolution of the instrument is 1.4nm for 350-1000nmand 2nm for 1000-2500nm. A square piece of dark black paper was utilized to place the soil samples. Each soil samples were of 250g. This instrument utilizes a halogen light as a light source for enlightening the samples. Using 8° field-of-view of fiber-optic cable the reflected light was gathered. Reflectance spectra of the soil samples was collected with the wavelength beginning from 350nm to 2500nm using the RS3 Spectral Acquisition software. A standardized white Spectralon panel has 100% reflectance and was utilized to enhance signal and calibrate accuracy. We took 10 progressive scans for each soil samples.

As we have total 30 samples of soil and every single sample was examined ten times, so total 300 soil samples we got from various regions. Statistical mean of the 10 scan was obtained using the View Spec Pro software and it was recorded as the spectral reflectance of the specific soil sample.

D. Data Pre-processing:

These spectral signatures recorded were in ASD format. Spectral signature then transformed into ASCII format and then to .xlsx format for further analysis. Using RS3 software, we gathered all spectral signatures of samples and that signatures were pre-processed with the help of software view spec pro. Spectra pre-processing is considered as an essential part. A few spectra pre-processing strategies were applied on the spectral data including first derivative, Savitzky Golay filtering [16].

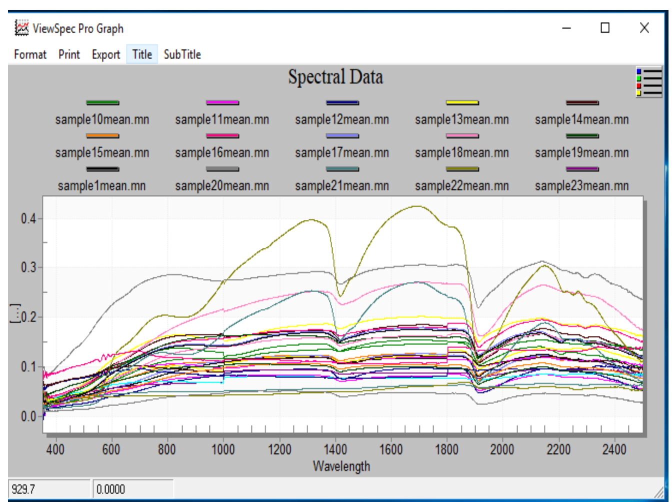

Figure 1. Mean spectral signature of all 30 samples

E. Data Modeling:

A total of 30 samples were randomly divided into two sets such as calibration which consists of 22 samples and validation (testing) which consists of 8 samples. The predictions of iron oxide were based on cross-validation of all samples used in the calibration and afterward to test the accuracy of predictions with validation datasets. The calibration between reflectance of soil and its iron oxide content were carried out in Matlab R2017a via PLSR-based analysis approach.

F. Partial Least Square Regression:

PLSR is a generally satisfactory demonstrating strategy and is typically utilized in quantitative reflectance spectroscopy information investigations [17]. To build up a prediction model based on soil spectra, the Partial least square regression (PLSR) method was applied to find a few linear combinations clarifying most of the variation in both predictors (X, spectra) and responses (Y, soil property)[18]. The partial least square regression technique was utilized to set up relations between reflectance spectra and estimated soil factors. Because of its advantage of measurement decrease, synthesis, and tackling colinearity issues among independent variables , partial least squares regression(PLSR) has been demonstrated as a vigorous and solid methodology in spectral quantitative research [19-22].

G. Prediction Precision Appraisal of Models:

The parameter root mean square error (RMSE) was utilized to assess the prediction results. Coefficients of determination (R^2) were computed for reliability of prediction. The best model was picked as the one demonstrating the lowest root mean square error (RMSE) and the highest coefficient of determination (R^2).

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(Ym - Yp)^2}{\sum_{i=1}^{n}(Yi - Ymean)^2}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Yp - Ym)^2}$$

where Ym - measured value of Iron Oxide, Yp - predicted value , Ymean - mean of measured values, n - no. of measured/predicted values with i = 1, 2, 3,…,n.

IV. RESULTS AND DISCUSSION

PLSR model is used to predict iron oxide from reflectance. PLSR considers the entire spectral signature and diminishes to give few components further estimating iron oxide. PLSR examination is done in MATLAB® programming to build up connection between soil iron oxide and hyper spectral data. After applying first derivative pre-processing to data, R^2 of 0.91 and RMSE of 0.008711 were observed for calibration and R^2 of 0.92 and RMSE of 0.001624 were observed for validation. It is shown in figure 2.

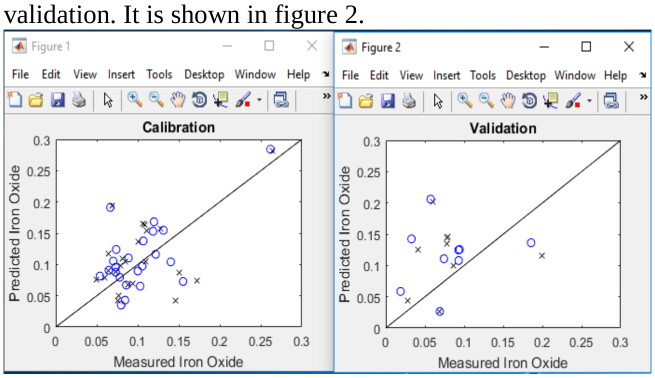

Figure 2. Calibration and Validation Using First Derivative

In case of Savitzky golay filtering R^2 of 0.87 and RMSE of 0.004415 were observed for calibration and R^2 of 0.89 and RMSE of 0.004209 were observed for validation (Fig. 3). We picked the model which is best for iron oxide forecast on the basis of model yielding the lowest RMSE value. It can be derived that iron oxide can be predicted to an acceptable level of accuracy.

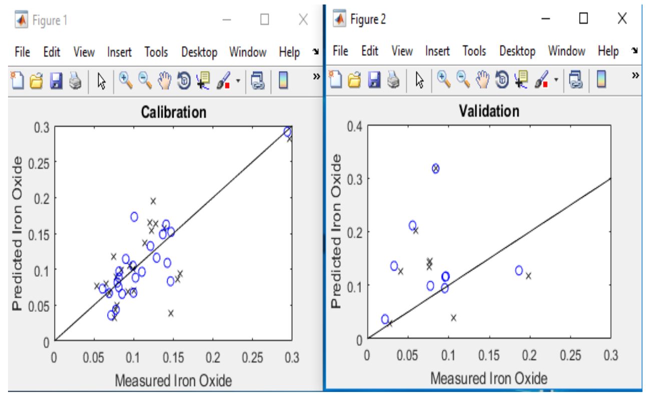

Figure 3. Calibration and Validation using Savitzky Golay

Besides this we already took 4 samples who weigh 100g each which are same as one of the 4 samples previously collected only difference is that previously collected samples are of 250g. This is done just to verify the spectra, whether weight of samples impacts spectra or not. The percent of iron oxide for all collected samples are as follows:

Table 1. % of Iron Oxide content for all 30 samples

No. of Samples	% of Iron Oxide	No. of Samples	% of Iron Oxide
Sample-1	0.0031	Sample-16	0.0068
Sample-2	0.0077	Sample-17	0.0036
Sample-3	0.0020	Sample-18	0.0024
Sample-4	0.0011	Sample-19	0.0024
Sample-5	0.004	Sample-20	0.015
Sample-6	0.0024	Sample-21	0.0016
Sample-7	0.0068	Sample-22	0.0068
Sample-8	0.0052	Sample-23	0.0048
Sample-9	0.0072	Sample-24	0.0044
Sample-10	0.0124	Sample-25	0.0044
Sample-11	0.0036	Sample-26	0.0048
Sample-12	0.0076	Sample-27	0.0044
Sample-13	0.0064	Sample-28	0.0011
Sample-14	0.006	Sample-29	0.002
Sample-15	0.0024	Sample-30	0.0016

V. CONCLUSION

Being as one of the essential nutrient in the soil, Iron Oxide is necessary for the production of crop. In this study, we have identified the iron oxide content in soils from the Jalna district of Maharashtra state utilizing the VNIR reflectance spectroscopy. In this study to capture the spectra of the gathered soil samples we used ASD fieldspec4 instrument. with the help of acquired spectral signature we got 444nm, 480nm, 529nm, 680 nm, 880nm, 920nm wavelengths showing major reflectance for iron oxide content. This study suggests that Vis-NIR spectroscopy combined with PLSR can estimate iron oxide with an acceptable level of precision. Vis-NIR spectroscopy offers a viable, simple furthermore, quicker procedure to anticipate iron oxide in soil.

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