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Research Article

ESTIMATION OF COPPER CONTENT IN AGRICULTURAL SOILS BY VNIR SPECTROSCOPY USING FIELDSPEC4 SPECTRORADIOMETER

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ABSTRACT

There is a huge problem of soil pollution throughout the world. Its results lead to thrashing of environment and health. So it is important to know about soil quality with metals. This research aims to identify content of copper within soil samples using FieldSpec4Spectroradiometer (Analytical Spectral Devices, Inc., USA). The instrument ASD FieldSpec4 Spectroradiometer is used for gathering spectral signature of soil samples collected from different agricultural lands in Aurangabad district of Maharashtra state in India. We used Partial Least Squares Regression (PLSR) to calculate the expected reflectance spectroscopy in the VNIR ranges to identify the copper content in the soil samples. It is used with several spectral preprocessing techniques including first derivative and Savitzky-Golay smoothing, Absorbance, Standard Normal Variate and Continuum Removal. Then, the expected results were evaluated by relative root mean square error (RRMSE) and coefficients of determination (R2). According to the criteria of minimal RRMSE and maximal R2, the observations using the PLSR models with the FD pretreatment was (RRMSE =0.0008-0.1453, R2 =0.9987), SNV pretreatment was (RRMSE= 0.0004,R2 =0.9793), and CR pretreatment was (RRMSE =0.0003 , R2 =0.9789). Wavebands at around 650-700 nm and 900-1000 nm were selected as important spectral variables to construct final models. The correlation analyses and regression results in the PLSR models both suggest that the main mechanism for estimating Cu content in this case study lies in its correlation with Fe content. In conclusion, concentrations of copper in soils could be indirectly assessed by soil spectra, therefore, spectral reflectance would be an alternative tool for monitoring soil heavy metals contamination.

INTRODUCTION

Soil is an important resource for the survival of plants, animals and human races. Doran and Park in defined soil quality as "the capacity of a soil to function, within ecosystem and land use boundaries, to sustain productivity, maintain environmental quality, and promote plant and animal health", a definition that includes an inherent and adynamic component[1][2].

However, soil is being threatened by increased natural and human induced activities. Degradation of soil leads to a reduction or complete loss of its ecological and productive values. It is caused primarily by chemical pollution, especially with excessive, unnatural amounts of trace elements such as cadmium, lead, zinc and copper, which may disturb the function of the complex system of processes occurring in the soil, and cause negative changes in biological activity and physical properties of the soil[3].

Copper belongs to elements whose natural content in the soil is most considerably exceeded. Copper is an important element for normal growth of living things, but both its excess and deficiency are harmful. Copper deficiency in the diet may cause anaemia, insufficient growth, fertility problems, nervous system disorders and circulatory system diseases. Its excess may lead to changes in the liver and damage kidneys, brain tissue, coronary vessels and myocardium. Soils high in organic matter and weathered, sandy soils are likely to be deficient in copper. A great deficiency may cause serious stunting of growth and visible symptoms of disease in plants, but moderate deficiency may merely reduce yields [3]. Therefore, this study was conducted to assess Cu concentrations in croplands, to evaluate the feasibility of reflectance spectra in the rapid prediction of Cu content in the soils.

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MATERIALS AND METHODOLOGY

Study Area: The Soil Samples were collected from different agricultural lands in Aurangabad District of Maharashtra state in India. Aurangabad is in Maharashtrastate to the west of India. It is located at 19° 53' N and 75° 23' E having annual mean temperature of 17°C to 33°C. A total of30 samples were collected for the study. Soil samples were collected from the plough layer (0-20 cm) and stored in an air-tight plastic bag. The samples were air dried for two to three days under normal room temperature. Small pieces of stones, root debris, and plant parts in the soil samples were removed by hand picking before analysis. Large lumps were broken down. Then the soil was sieved through 2mm sieve and taken for measurements to the laboratory.

Spectral Measurements and preprocessing: The FieldSpec4 Spectroradiometer was used for measurements of soil samples in the Geospatial Lab, Dept. of CS & IT, Dr. B. A. M. University Aurangabad, Maharashtra, India. To minimize the influence of external light, the spectra scanning procedure was carried out in a dark room. The sampling interval and spectral resolution of the instrument is 1.4nm for 350-1000nmand 2nm for 1000-2500nm. Spectral Reflectance of the soil samples was collected with the wavelength starting from 350nm to 2500nm using the RS3 Spectral Acquisition software. A light source matched with the spectroradiometer was used with a 45 incident angle. A square pieces of black paper with side lengths of about 35cm were used in turn to hold the soil samples. About 200 g of soil samples panning a diameter of approximately 20 cm was scanned by the spectroradiometer at a distance of 30cm from probe to sample surface and a zenith angle of 90 . The distance between gun and the light source was 60cm.

A standardized white Spectralon panel has 100% reflectance and was used to optimize signal and calibrate accuracy and detector responses. The spectral radiance over it was measured every 10 samples. Then spectral radiance of the soil sample was measured. Approximately 10 scans were made for each sample. Statistical mean of the 10 scan was acquired using the View SpecPro software and it was recorded as the spectral radiance of the particular soil sample. Spectral radiance was exported in ASCII format and then to .xlsx format for further analysis.

All the spectra preprocessing and processing was carried out in Matlab7.12.0 (R2011a) software. Spectra preprocessing is considered as an integral part. Transformations onpredictors could be useful for model calibration. Several spectra preprocessing techniques were applied on the spectral data including first and second derivative, Savitzky Golay filtering with 11 points and a second-order polynomial, absorbance (log [1/reflectance]), first and second derivative of absorbance, standard normal variate (SNV), and continuum removal (CM).[4].

Data Analysis

The partial least square regression technique was used to establish relations between reflectance spectra and measured soil variables [11][12]. This technique makes use of all variables and compresses them into a few principal components (PCs) comprising some highly interrelated variables [13][14]. It is based on latent variable decomposition of two variable blocks, matrices X and Y that contain spectral data and soil characteristics, respectively. However, the purpose of this technique is to find a small number of latent factors that are predictive of Y and use X efficiently. For all 30 samples, cross-validation of leave-one-out method was used to verify the

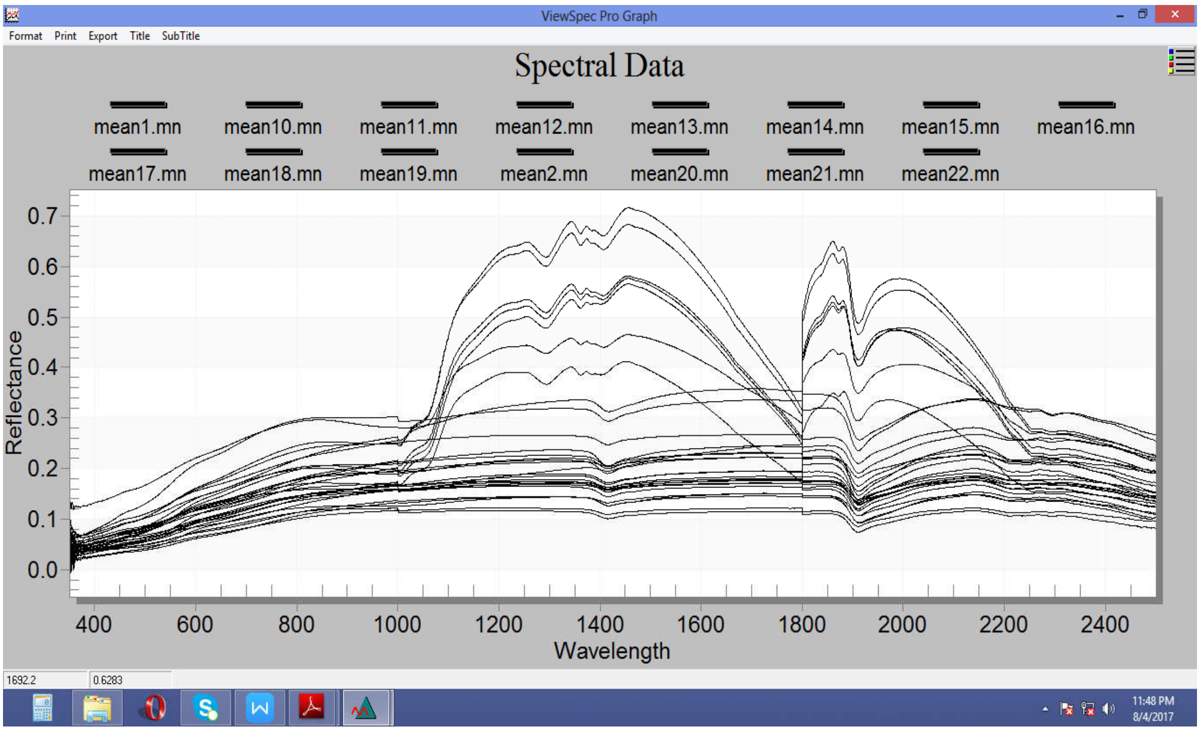

Fig 1 mean spectral data of 30 soil samples

Table 1 Relative root mean square error (RRMSE), coefficients of determination (R2) of the partial least square regression models

	Pre-treatment	R2	RRMSE
1.	First derivative	0.9987	0.0007
2.	Second derivative	0.9953	0.0020
3.	Savitzky Golay Filter	0.5985	0.0001
4.	Absorbance (log10/reflectance])	0.9935	0.3398
5.	First derivative absorbance	0.9522	1.8115
6.	Second derivative absorbance	0.9481	0.1225
7.	Standard Normal Variate	0.9793	1.2557
8.	Continuum Removal	0.0003	0.9789

prediction capability of the PLSR models for the training set. At each time, all n samples were formed within a dataset, n¡1, to develop the regression model. Based on such a model, values of the properties of the soil sample not used in developing the models were predicted. This procedure was repeated for all samples (n), resulting in predictions for all samples. The parameter root mean square error (RMSE) was used to evaluate the prediction results [20]:

$$RMSE=\sqrt{\frac{\sum(ym-yp)2}{n}} \qquad \text{--------------------(1)}$$

where ym is the measured value for a soil parameter and yp is the predicted value by the PLSR model. Coefficients of determination (R2) were calculated for reliability of prediction. For clarity of comparison, RMSEs were divided by the mean value of soil properties and shown as relative RMSE (RRMSE).

RESULT AND DISCUSSION

The results obtained after applying PLSR on the spectral data is stated in Table1. Wavelengths around1900 nm and 2200 nm were known as diagnostic features of water [15] and which vary under different moisture conditions. Therefore, wavelength regions of 650-700 nm and 900-1000 nm were considered to be particularly useful for Cu estimation in this case. Both of these regions were representative of absorptions due to iron oxides, such as hematite and goethite [16]. Therefore, the mechanism of estimating Cucontent was assumed to lie in its correlation with Fe content.

CONCLUSION

In this study, we have identified the copper content in agricultural soils from the Aurangabad district of Maharashtra state using the VNIR reflectance spectroscopy. The feasibility of estimating copper content from soil samples collected from different agricultural lands in Aurangabad district of Maharashtra state is possible with VNIR reflectance spectroscopy (350nm-2500nm). It can be concluded that VNIR reflectance spectroscopy coupled with PLSR model could be an effective model for estimating other metal concentration in agricultural soils.

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