Predicting Lead and Nickel Contamination in Soil using Spectroradiometer

Bharati S. Pawar, Ratnadeep R. Deshmukh

***Abstract:** In the geosciences, visible–near–short-wave infrared reflectance spectroscopy seems to have the capability to become a helpful technique for soil classification, mapping, and remote confirmation of soil characteristics and mineral composition. Focus on improving the spatial resolution of soil maps in order to better deal with localized problems like soil pollution. A variety of physio-chemical properties were measured in long-term spiked soils with a range of lead and nickel concentrations and also their spectral reflectance between 400 and 2500 nm at three different locations in the agricultural region of MIDC, Aurangabad, Maharashtra, India. Principle component analysis (PCA) used for feature extraction of soil were partial least squares regression (PLSR) method is used for classification. To measured amount of lead and nickel in soil sample, thirteen features of soil samples are calculated. The main aim of this study was to use statistical methods to calculate the lead and nickel concentrations in soil, as well as to assess the efficiency of VNIR-SWIR reflectance spectroscopy for heavy metal estimation in soil using the ASD FieldSpec4 Spectroradiometer.* R^2 *= 0.96 provides the best precision for lead content and* R^2 *= 0.95 for nickel content in soil, according to the findings. Lead and nickel have RMSEs of 3.396 and 2.680, respectively. The outcomes show that the proposed method is capable of accurately forecasting lead and nickel concentrations.*

***Keywords:** Agricultural Soil, ASD Fieldspec-4, Heavy Metals, PCA, PLSR, RS-GIS.*

I. INTRODUCTION

Heavy metal contamination of soil has been a serious environmental issue, especially in countries that are rapidly industrializing and urbanizing. Metal pollution from mines and smelters are thought to pose a serious threat to human health around the world [1]. In this technological age, The RS-GIS is progressing at a breakneck pace, with numerous applications in the agricultural sector as well as other industries that depend on agriculture. At very low concentrations, nickel (Ni) is an essential micronutrient. In high amounts, however, it is poisonous. Chemical fertilizers, pesticides, and fungicides are commonly found to contain Pb [2]. Pb and Ni is a toxic heavy metal that is listed by the World Health Organization as one of the top ten most dangerous chemicals for public health [3].

Soil spectroscopy has been used as a quick tool for predicting heavy metals in soil. VNIR-DRS (Visible and Near Infrared Diffuse Reflectance Spectroscopy) has grown in popularity among soil scientists over the last two decades. In terms of physical and chemical properties of soil, soil is the primary source of crop nutrients, and one of its most important characteristics is spectral reflection. Some researchers have examined that spectral reflectance characteristics is depends upon soil properties, surface condition and soil moisture using various analytical techniques [4].

A. VNIR-SWIR Reflectance Spectroscopy

VNIR-SWIR is an acronym for Visible and Near Infrared – Shortwave Infrared. Reflection Spectroscopy is more effective than other methods as well as it is less expensive and quicker process [5]. It can be used as a replacement to traditional laboratory procedures. [6, 7]. Diffuse Reflectance Spectroscopy (DRS) sensors have visible range 400-700nm and near infrared range 700-2500nm. DRS sensors are more effective at providing fast spatial data with low cost and high resolution. The technique of VNIR Spectroscopy offers descriptive and analytical details about soil [8]. Soil spectral reflectance characteristics are defined as a function of wavelength by their absorbance or reflectance in the electromagnetic spectrum. This analysis used the Analytical Spectral Device (ASD) FieldSpec4 Standard-Res Spectro-radiometer to capture the spectral reflectance of soil samples. ASD Fieldspec4 well-suited to the needs of today's researchers.

B. Study Objectives

The goals of the study was to first Using spectral data obtained in the lab using an ASD Fieldspec4 Spectroradiometer, evaluate the efficiency of VNIR-SWIR reflectance spectroscopy for predicting lead and nickel in soil samples by collecting spectral measurements. Second using a statistical approach and regression model to assess the spectral spectrum of lead and nickel, as well as their properties, and third estimation of lead and nickel contamination develop a tool.

There are five parts of the current article. The research's basic introduction, reflectance spectroscopy, and objectives are described in the first section, along with a background analysis. The study location, soil sampling, and database selection using reflectance calculation are all covered in the second portion. The experimental and statistical analyses are highlighted in the third section. The fourth portion of the paper included a systematic discussion of the study's findings. The fifth segment concludes with a discussion of potential prospects.

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II. MATERIALS AND METHODOLOGY

A. The Study Site

Twenty-eight (28) soil samples were obtained at three separate locations in the MIDC district of Aurangabad, Maharashtra, India. With latitude value of 19.85133 and longitude value 75.26255. Wadgaon Kolhati MIDC area agricultural field, Aurangabad, Maharashtra (location 1), Samruddhi highway roadside agricultural field 1 and field 2 (locations 2 and 3) from Aurangabad city were included in the report. To keep the moisture of the soil samples, each sample was placed in an airtight plastic bag and labeled with the collected data, as well as the latitude and longitude values along with the city. For measurements of all 28 soil sample very first sieved soil samples through a 2mm sieve. Because of these visible roots were get removed. Figure II.1 shows the graphical position of the research site.

B. Soil Sampling

Using the RS3 Spectral Acquisition software and the ASD FieldSpec4, database for 28 soil sample were collected. The spectrum of soil samples was generated by averaging 10 successive scans of 28 soil samples. Using the View Spec Pro Version 6.2 program, the reflectance of each soil sample was graphed and pre-processed.

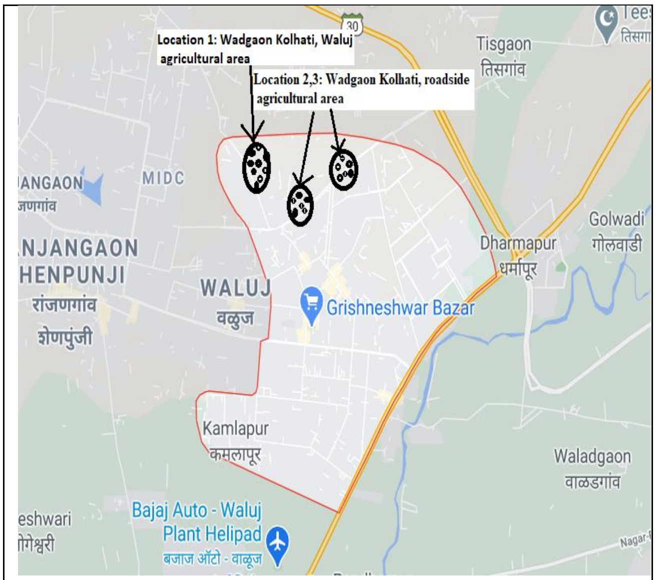

Fig II.1 Geographical Location of collected 28 soil samples.

The soil samples were scanned using the ASD Fieldspec4 Spectroradiometer, having 350-2500 nm spectral range. Fig II.2 shows the Database collection on Field-Spec-4 Spectroradiometer. We took the white reference of every sample using a standardized white Spectral on panel with 100 percent reflectance for the purpose of optimization. White reflectance has been taken to avoid errors in reflectance spectra. Optical lens have 8 degree FOV. Optical lens have placed with height 5cm above on the soil sample, and the light source was placed at a 45 degree angle [9]. Measurements of soil samples were taken in black dark room. Because of in black dark room irradiance conditions we can better monitor.

C. Reflectance Measurement and Database Collection

The ASD FieldSpec4 Spectroradiometer produces a spectrum of 1.4nm (350-1000nm) and 2nm (1000-2500nm) resolution, as well as 2151 bands with a uniform spectral interval of 1nm [10]. View-Spec Pro is a data analysis program that displays data as a graph.

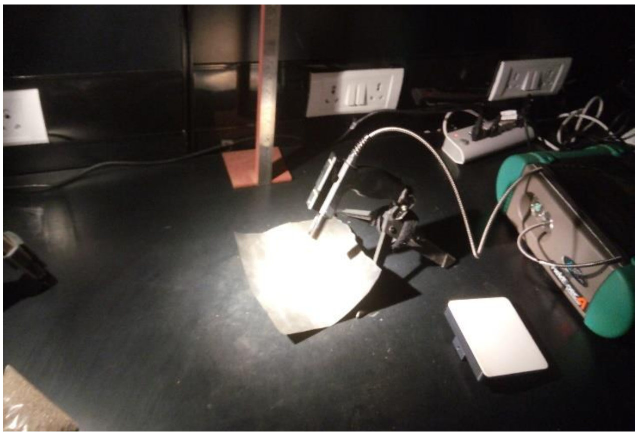

Fig II.2 Database collection using Field-Spec-4.

For statistical analysis View-Spec Pro program allows pre-processed the .asd files. These .asd files are used as input values for viewing graph data. Using the View-Spec Pro program, the statistic mean spectral reflectance of 28 soil samples was calculated. Absorption peak for lead is 578nm-708nm and for nickel 495nm to 680nm observed in previous research [11, 12].

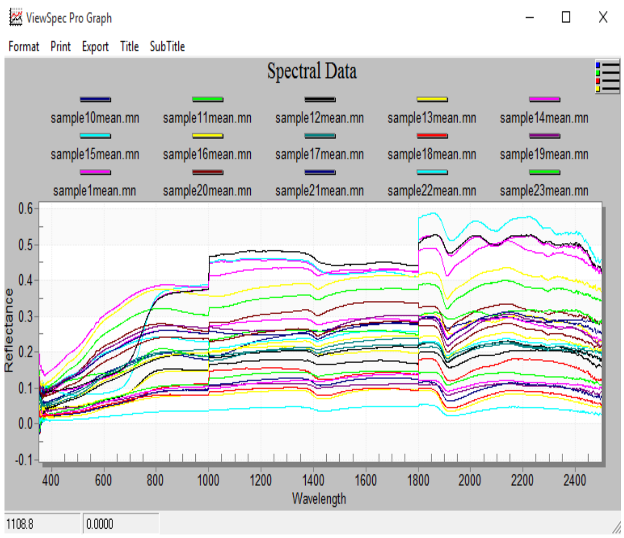

Fig II.3 Statistic mean spectral reflectance of 28 Soil samples.

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In ViewSpec Pro softwere preprocess data displayed. for displaying these data ViewSpec Pro softwere convert each spectral signature to ASCII format.

III. EXPERIMENTAL SECTION

A. Soil Physiochemical Analysis and Spectral measurement

To assess the expected data of soil texture, such as lead and nickel, we used chemical testing in a soil testing laboratory prior to heavy metal analysis in soil using spectral measurement. In the soil testing lab at MIT college in Aurangabad, heavy metal content in soil is determined. According to previous research, Vis-NIR Diffuse Reflectance Spectroscopy gives faster, better prediction and low costly than conventional laboratory methods or field soil sampling. [13].

B. Statistical Analysis

1. Partial Least Square Regression

The Partial Least Square Regression approach is a very good and has become the most common regression technique for multivariate data analysis (PLSR). The PLSR has proved to be a standard instrument in the field of soil spectroscopy. Multi - collinearity and high dimensionality problem can be solved using the PLSR method.

The multi-dependent variables to multi-independent variables PLSR modeling method is useful for detecting noise in the system by filtering and decomposing the data and extracting comprehensive variables. In cross-validation, for calibrating the PLSR model for soil property, the Root Mean Square Error (RMSE) was used as the decision criterion. VNIR-DRS soil texture prediction models were developed using Principal Component Analysis (PCA) and Partial Least Square Regression (PLSR) models from the calibration package.

2. Principal Component Analysis

The number of mathematical components that represented the data set was determined using Principal Components Analysis (PCA) of the spectral data. Principal Component Analysis (PCA) was used to scale down the dimensionality of data beyond the abundance of lack of detail. It's a statistical technique for converting a number of potentially connected variables into principal components, or a set of values for linearly unrelated variables [14]. The orthogonal transformation is used to describe a linear-independent spatial pattern.

IV. RESULT AND DISCUSSION

Lead and nickel heavy metals were found in all twenty-eight (28) soil samples. For calibration and validation 28 soil sample divided in two groups. For calibration 18 soil samples and for validation 10 soil samples. [15,16]. It has been verified that there are major unique bands for lead around 578 to 708nm and for nickel around 495 to 680 nm for determining heavy metals, such as lead and nickel, in soil samples collected[17]. We measured the reflectance of soil samples with an ASD FieldSpec4 Spectroradiometer. The PCA values for lead and nickel were calculated and found to be 0.000548 and 0.000607 respectively.

Table I. Static information for soil Lead and Nickel Concentration (mg/kg) in the study areas

Heavy Metal Class	Group	Min	Max	Mean	Median	Variance	SD	CV
Lead	Calibration set(n=18)	22.9	60.9	34.12	28.1	122.796	11.08	0.347
	Validation set(n=10)	24.1	61.3	42.51	34.7	159.13	12.61	0.296
	Entire Dataset(n=28)	22.9	61.3	38.315	30.2	144.359	12.014	0.3136
Nickel	Calibration set(n=18)	19.91	42.42	29.57	29.82	58.1	7.622	0.2577
	Validation set(n=10)	16.35	39.98	22.899	21.12	50.151	7.082	0.3092
	Entire Dataset(n=28)	16.35	42.42	26.24	25.5	74.226	8.615	0.3283

The linear fitting plots in Fig IV.1 display the measured effects of lead and nickel features, respectively. The graph depicts the 13 characteristics that were determined using the regression methodology for classification. PCA was used to extract features and PLSR was used to classify the soil heavy metals. On the y axis is the accurate fitting likelihood, and on the x axis is the data. The values show how the linear fitting plot correlates with the measured effects.

The determined parameters for lead and nickel are shown in Table II. It shows the results of the current study's final simulation, including PCA, R^2, and RMSE values.

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Heavy Metal Type	PCA	R^2	RMSE
Lead	0.000548	0.96	3.396
Nickel	0.000607	0.95	2.680

Table II: The determined parameters for lead and nickel

The Fig 4 and 5 shows the analysis of 13 features of soil. Using bar charts, the measurement of 13 features measured in this review of lead and nickel.

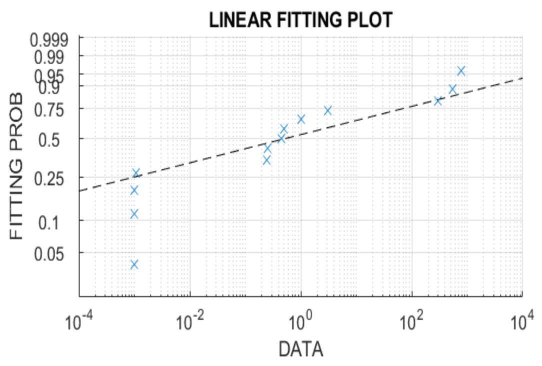

Fig 4: Measured features of Lead plotted as a linear fitting plot.

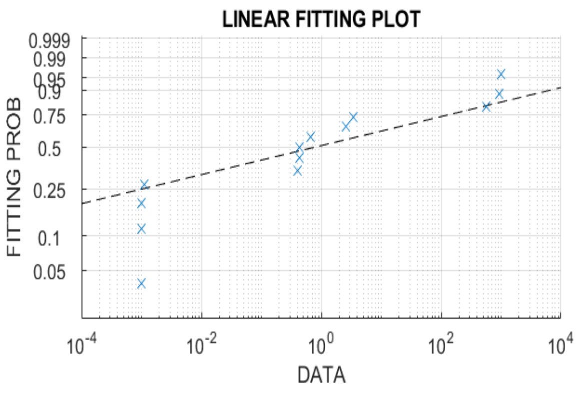

Fig 5: Measured features of Nickel plotted as a linear fitting plot.

13 features are Integrated EMG, Simple Square Integral, Mean Absolute Value, Variance of EMG, Autoregressive coefficients (AR), Waveform length, Mean Absolute Value Type1, Modified Mean Absolute Value Type 2, Root Mean Square, Difference absolute standard deviation value (DASDV),Hjorth Mobility, Hjorth Activity, and Hjorth Complexity. Using above features calculated values for lead and nickel easily differentiate.

By comparing other approaches, PCA and PLSR techniques yield more accurate results.

	Predicted			User Accuracy (Precision)
	Lead	**Nickel**	**Classification Overall**	
Lead	26	2	28	92.857%
Nickel	2	26	28	92.857%
Truth Overall	28	28	56	
Producer's Accuracy	92.857%	92.857 %		

Therefore,

% Accuracy = 92.857%

Kappa coefficient = 0.857

As a result, the suggested approach produces the best results with 92.857 percent accuracy.

V. CONCLUSION AND FUTURE SCOPE

The proposed research represents lead and nickel in soil prediction using regression technique to increase efficiency and accuracy. In this research, we used two methods for feature extraction and classification: PCA analysis and the PLS regression algorithm. Lead and nickel in soil are determined by the regression's production. This study found that the VNIR-SWIR reflectance spectroscopy method is critical for determining lead and nickel levels in soil because it is fast and produces more accurate results than traditional laboratory methods. R^2 = 0.96 for lead and R^2 = 0.95 for nickel, according to the results. This research provides superior results for precision farming practices and agricultural decision-making. Large number of samples gives more accurate result.

The vast area for research, as well as more soil samples, will be considered in the potential scope for creating more successful predictive models and more other polluted heavy metals in soil.

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