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Analysis of Soil Iron Oxide in Lateritic Soil by Spectral Method: A Review

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Abstract

The primary purpose of this research is to learn more about the properties of soil using Vis-NIR spectroscopy. The spectral signature of obtained soil samples is captured using the ASD FieldSpec4 Spectroradiometer equipment. In the Vis-NIR wavelength range, utilized Partial Least Squares Regression (PLSR) method was used to estimate the properties present in the samples of soil. Root mean square error (RMSE) and coefficients of determination were used to evaluate the results (R2).

Keywords: *Iron oxide, Plsr, Spectroradiometer, Soil*

INTRODUCTION

Laterite is a high-iron, high-aluminium soil and rock that is thought to have originated in hot, humid tropical environments. This soil has a rusty red colour due to the significant iron 69oxide .content. Weathering of the parent rock causes them to develop. Its chemical composition varies widely depending on its origin, climate conditions and age. Lateritic soil has a high concentration of Fe and just a moderate proportion of Al [16].

Why laterite

Studies of laterites are important because of their economically viable concentrations of iron, nickel, gold, phosphate, aluminium, titanium, manganese, and rare earth components. Laterite is a mineral that may be used to determine soil fertility, agricultural suitability, and geological age. Lateritic

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soil is conducive to plant root hairs and can absorb other diffused nutrients from the water. It can be used to make fertilizers and food for aquarium plants. Fish ponds in lateritic soil zones exhibit low availability of phosphorus, resulting in a restricted accumulation of various fish food organisms.[16]

In farming, accurate knowledge of soil nutrients is critical for crop development. The chemical, biological, mineralogical, and physical properties of soil have been mentioned by several authors [1]. Iron oxides are significant soil pigments that have an impact on plant nutrient uptake. Iron oxide estimation using traditional methods is time-consuming and expensive. Remote sensing and reflectance spectroscopy are excellent alternatives that may be utilized to replace traditional soil examination procedures.

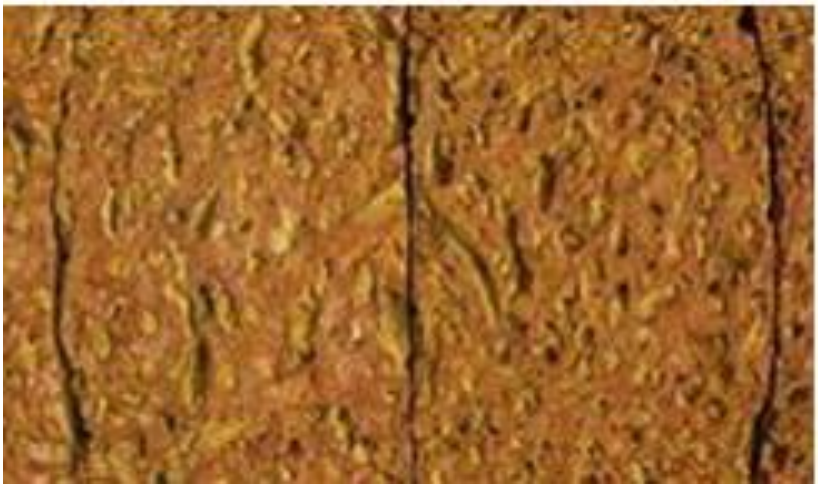


Fig 1: Laterite rock



Fig 2: Laterite rock

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To connect spectral reflectance to observed material parameters, many calibration procedures have been applied. The most utilized multivariate calibration techniques are Principal Components Regression (PCR), Partial Least Squares Regression (PLSR), Stepwise Multiple Linear Regression (SMLR), and Artificial Neural Network (ANN) [2].

LITERATURE REVIEW

Rossel et. al. (2007) [3] examined the visible, near-infrared (NIR), and mid-infrared (MIR) spectra to predict soil parameters. Soil pH, lime requirement (LR), organic carbon (OC), clay, silt, sand, cation exchange capacity (CEC), exchangeable calcium (Ca), exchangeable aluminium (Al), nitrate-nitrogen (NO3–N), phosphorus, exchangeable potassium (K), and electrical conductivity were all taken into consideration (EC). For OC, the PLS calibration model produces excellent results. For prediction, the coefficient of determination (R2) ranges from 0.97 to 0.73.

Richter et al. (2009) [4] proposed a model for identifying iron oxide in red Mediterranean soils using the Fe-NIR absorption band and a spectrum analysis of the spectral influence of different soil textures on the soil reflectance Fe-related absorption bands. They discovered that iron oxide absorption bands in clay-dominated soil samples were generally deeper than in sand-dominated soil samples with similar iron oxide levels. Both sample models were shown to have minimal prediction errors (sand: R2 = 0.87, RMSE = 2.72; clay–silt: R2 = 0.70, RMSE = 4.13).

Kusumo et. al. (2011) [5] investigated the use of proximate sensing to predict maize root density and soil characteristics (carbon and nitrogen) using visible and near-infrared (Vis-NIR) spectral reflectance. The coefficient of determination (R2) 0.86 for carbon and nitrogen (0.81) in the PLSR calibration model indicate very good results for root density 0.75.

Curcio et.al. (2013) [6] used VNIR spectroscopy to successfully measure soil texture dispersion in the laboratory. The potential of visible and near-infrared (VNIR, 400–1200 nm) and shortwave infrared (SWIR, 1200–2500 nm) to predict silt, sand, and the authors assess clay. For the analysis, a wavelength range of 400–2500 nm was chosen. The outcome demonstrates the high potential for predicting silt, sand, and clay. The calibration coefficients of determination

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(R2) for silt, sand, and clay were reported to be 0.60, 0.80, and 0.87, respectively.

Changkun Wang et.al (2017) [7] looked at the viability of using visible and near-infrared (Vis-NIR) reflectance spectroscopy to determine rare earth elements (REE) in soil. To record soil spectra, they employed a Field Spec 4 Hi-Res spectrometer. Inductively coupled plasma-mass spectrometry (ICP-MS) and emission spectrometry (ICP-ES) were also used to determine REE levels. The soil spectra and reference values of REE obtained by ICP-MS were calibrated using PLSR. The results suggest that Vis-NIR reflectance spectroscopy is a viable method for determining REE in the soil in a simple and quick manner.

Chutipong et.al. (2017) [8] conducted research on near-infrared spectroscopy (NIRS) for SOM prediction in the paddy area and prediction of total nitrogen. The results of this study demonstrate that NIRS is an effective method that can be used to predict SOM and total nitrogen. SOM had a coefficient of determination R2 of 0.73, while total nitrogen had a coefficient of determination R2 of 0.72.

Nisha Bao et.al. (2017) [9] evaluated the SOM by physio-chemical analysis and visible-near and shortwave infrared reflectance spectroscopy. Wavelengths of 350–2500 nm have been used for analysis. The result shows the high predicting accuracy for SOM. The coefficient of determination, R2, is 0.95.

Gomez and Coulouma (2018) [10] explained the importance of laboratory VNIR/SWIR spectroscopy for predicting soil properties (clay and calcium carbonate) and analyzed regional model performances for soil property prediction at regional and within-field extents. A predication model was built using the partial least square regression (PLSR) method. The results showed that the regional extant predication model was accurate and within the field. The extent depends on model robustness.

Vibhute et.al. (2018) [11] investigated soil attributes through VNIR and correlated them with reflected spectra and detected SPA. The detected soil attributes were soil organic carbon, nitrogen, soil organic matter, pH, electrical conductivity, phosphorus, potassium, iron, sand, silt, and clay. A partial least squares regression (PLSR) model was built for the prediction of soil physicochemical properties. The coefficient of determination (R2) for soil organic carbon (0.89), nitrogen (0.68), soil organic matter (0.93), pH (0.82), electrical

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conductivity (0.89), phosphorus (0.98), potassium (0.82), iron (0.94), sand (0.98), silt (0.90), and clay (0.69).

Kayande et. al. (2018) [12]: The researchers used Vis-NIR spectroscopy to evaluate the iron oxide content in soil using ASD FieldSpec4 equipment. The root means square (RMSE) and coefficients of correlation were used to evaluate the results (R2). PLSR models with first derivative pre-processing were used to make the observations (RMSE =0.008711, R2 =0.91 for calibration; RMSE=0.001624, R2 =0.92 for validation). The wavelength bands 444nm, 480nm, 529nm, 680nm, 880nm, and 920nm are susceptible to soil iron oxide.

Vipin et.al. (2020) [13] used the visible (350-700), NIR (700-1100), and SWIR (1100-2500) spectral ranges to predict the chemical properties of nitrogen, phosphorous, potash, carbon, pH, as well as physical properties of sand, silt, clay, and soil organic matter (SOM) present in the soil. The coefficient of determination (R2) was 0.83 for silt, sand, clay, and 0.91 for SOM, 0.80 for moisture, 0.84 for pH, 0.83 for carbon, nitrogen, and potash, and 0.82 for nitrogen.

Pawar et al. (2021) [14] conducted a study in which they examined a number of physio-chemical parameters in long-term spiked soils containing a range of lead and nickel concentrations. They gathered 28 soil samples from three different locations in the Aurangabad district of Maharashtra, India. A partial least squares regression (PLSR) model was developed for the prediction of soil physicochemical parameters. According to the author, R2 = 0.96 provides the best precision for lead content in soil and R2 = 0.95 for nickel concentration in soil. The RMSEs of lead and nickel are 3.396 and 2.680, respectively. The results suggest that the proposed technique can forecast lead and nickel concentrations accurately.

Spectral Measurements using FieldSpec4: For soil sample assessments, the FieldSpec4 Spectroradiometer was employed. The spectral signature of each soil sample was obtained using an ASD Field Spec 4 spectroradiometer at Visible-Near Infrared wavelengths ranging from 350nm to 2500nm. The spectrum scanning method was carried out in a dark room to reduce the impact of outside light. The instrument's sample interval and spectral resolution for 350-1000nm, 1.4nm are used, and for 1000-2500nm, 2nm is used. Respectively.

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The soil samples were placed on a square piece of dark black paper. A halogen light source is used to illuminate the samples in this device. The reflected light was collected using the fibre-optic cable with an 8° field-of-view. The RS3 Spectral Acquisition software was used to obtain reflectance spectra of soil samples with wavelengths ranging from 350nm to 2500nm. To improve signal and calibrate accuracy, a standardized white Spectral on the panel with 100% reflectance was used, as well as 10 progressive scans for each soil sample. Using the View Spec Pro programme, the statistical mean of the 10 scans was calculated and recorded as the spectral reflectance of the specific soil. [15]

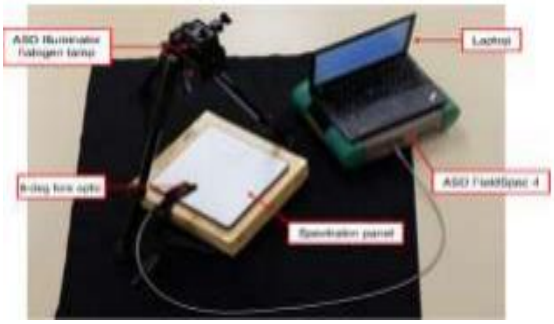


Fig 3: Spectroradiometer

CONCLUSION

The study above indicates that there are many various approaches for detecting soil iron oxide utilizing remote sensing and GIS therefore, it is feasible to identify iron oxide in soil using either reflectance spectroscopy or classical methods. Reflectance spectroscopy is a good choice among these methods that can be used to replace traditional soil analysis methods. In spectroscopy, the resulting reflectance is used to characterize the substance.

As a result, spectroscopy is an appropriate approach for determining the iron oxide concentration of soil. To connect spectral reflectance to observed attributes of materials, Principal Component Analysis (PCA) and Partial Least Square Regression (PLSR) are two examples of such approaches.

However, PLSR is a robust technique that accounts for both the x and y variables to estimate soil property and deals with the collinearity of predictor variables. So, based on the findings of the previous study, we discovered that visible and near-infrared reflectance spectroscopy is a quick and non-destructive analytical approach that requires little sample preparation and has been successfully utilized to detect soil parameters.

REFERENCES

1. White, K., Walden, J., Drake, N., Eckardt, F., and Settle, J. (1997). Mapping the iron oxide content of dune sands, Namib Sand Sea, Namibia, using Landsat Thematic

Page 28-35 © MANTECH PUBLICATIONS 2022. All Rights Reserved

Mapper data. Remote Sensing of Environment, 62, 30– 39.

2. Chang, C.W., Laird, D.A., Mausbach, M.J., and Hurburgh, C.R. (2001). Near-Infrared Reflectance Spectroscopy–Principal Components Regression Analyses of Soil Properties. Soil Sci Soc Am J, 65, 480-490.

3. Rossel, RA Viscarra, D. J. J. Walvoort, A. B. McBratney, Leslie J. Janik, and J. O. Skjemstad. "Visible, near-infrared, mid-infrared or combined diffuse reflectance spectroscopy for simultaneous assessment of various soil properties." Geoderma 131, no. 1-2 (2006): 59-75.

4. Richter, N., T. Jarmer, S. Chabrillat, C. Oyonarte, P. Hostert, and H. Kaufmann. "Free iron oxide determination in Mediterranean soils using diffuse reflectance spectroscopy", Soil Science Society of America Journal 73, no. 1,72-81,2009.

5. Kusumo, Bambang Hari, et al. "Measuring carbon dynamics in field soils using soil spectral reflectance: prediction of maize root density, soil organic carbon and nitrogen content." Plant and Soil 338.1 (2011): 233-245.

6. Curcio, D., et al. "Prediction of soil texture distributions using VNIR-SWIR reflectance spectroscopy." Procedia Environmental Sciences 19 (2013): 494-503.

7. Wang, Changkun, Taolin Zhang, and Xianzhang Pan, "Potential of visible and near-infrared reflectance spectroscopy for the determination of rare earth elements in soil", Geoderma 306,120-126,2017

8. Chutipong, Romsonthi, Tawornpruek Saowanuch, and Watana Sumitra. "In situ near-infrared spectroscopy for soil organic matter prediction in paddy soil, Pasak watershed, Thailand." Plant, Soil and Environment 64.2 (2018): 70-75.

9. Bao, Nisha, et al. "Assessing soil organic matter of reclaimed soil from a large surface coal mine using a field spectroradiometer in

Page 28-35 © MANTECH PUBLICATIONS 2022. All Rights Reserved

the laboratory." Geoderma 288 (2017): 47-55.

10. Gomez, C., & Coulouma, G. (2018). Importance of the spatial extent for using soil properties estimated by laboratory VNIR/SWIR spectroscopy: Examples of the clay and calcium carbonate content. Geoderma, 330, 244-253.

11. Vibhute, Amol D., et al. "Determination of soil physicochemical attributes in farming sites through visible, near-infrared diffuse reflectance spectroscopy and PLSR modelling" Ecological Processes 7.1 (2018): 1-12.

12. Kanchan Sukhdev Kayande., et al "Hyperspectral Analysis of Soil Iron Oxide using Fieldspec4 Spectroradiometer" Vol.-6, Issue-11, Nov 2018

13. Borole., et al "Soil properties assessment in surface and subsurface using spectroradiometer for raver tehsil of Jalgaon district" Journal of critical reviews ISSN-2394-5125 vol 7, issue 18, 2020.

14. Bharati S. Pawar, et al, "Predicting Lead and Nickel Contamination in Soil using Spectroradiometer" International Journal of Recent Technology and Engineering (IJRTE) ISSN: 2277-3878, Volume-10 Issue-1, May 2021.

15. Bhise Pratibha R. and Sonali B. Kulkarni, "Review on Analysis and Classification Techniques of Soil Study in Remote Sensing and Geographic Information System", IJETTCS, 2017.Veena, Bhargava. Textbook of Geography - Grade 1

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