

International Journal of Innovative Research in Science, Engineering and Technology

(An ISO 3297: 2007 Certified Organization)

Vol. 5, Issue 4, April 2016

Monitoring Arsenic Contamination in Agriculture Soil using Spectroradiometer

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ABSTRACT: There are different types of pollution. Soil Pollution is one of the serious problems in the world. Pollution affects on damage of environment, Health, Global Warming, Ozone Layer reduction, and Infertile Land. Soil contamination is caused by the human-made chemicals or other alteration in the natural soil environment. It is typically caused by industrial process, agricultural chemicals, or improper wastage. The most common chemicals involved are petroleum substances, polynuclear, aromatic hydrocarbons, solvents, pesticides, lead, and other heavy metals. Pollution is related with the degree of industry use and intensity of chemicals used.

The effect of this pollution on soil directly affects human health through direct contact with soil or through inhalation of soil contaminants which have vaporized. An effect comes to agricultural lands which have different types of soil contamination. Pollutant typically alter plant metabolism, often causes a reduction in crop yields. This paper states that work is done for possibilities of reflectance spectroscopy in the VNIR ranges to predict content of arsenic in soil samples.

KEYWORDS: Arsenic (As), OPLS, PLS, Reflectance Spectroscopy.

I. INTRODUCTION

Arsenic is a chemical element having symbol As. Arsenic observes in many minerals, usually in combination with metals and sulphur as well as a pure crystalline element. It is a metalloid. Arsenic toxicity is a medical condition caused by elevated levels of arsenic in the body. The important basis of arsenic poisoning is from ground water that naturally observes high concentrations of arsenic. A study in 2007 found that over 137 million people in more than 70 countries are usually affected by arsenic poisoning from drinking water. Arsenic effects start with headaches, severe diarrhea, confusion and drowsiness. The organs of body are usually affected by arsenic poisoning are the lungs, skin, kidneys, and liver. The last result of arsenic effects is coma and death. Toxic Elements concentrations in soils can be measured, but their occurrence based on large-scale sampling and scientific analysis techniques, which requires more time, not efficient, and expensive when applied on a large scale. Reflectance Spectroscopy gives useful option to traditional methods for soil elements analysis due to its convenience, accurate and rapidity. Since the past decades, arsenic (As) and copper (Cu) concentrations in the agricultural soils increased quickly and depressed the quality of crops such as rice. Human health is having threat of high metal pollution in soils and foods. Fortunately, more and more attention has been given to monitoring contamination of heavy metals in soils and estimation of its influence on agro ecosystems. Depending on physical or conventional chemical analysis techniques and large-scale sampling, Cu and As concentrations in soils will be measured, but the adverse importance is that they are time-consuming, less efficient, and much more expensive when applied at a huge scale in contaminated agricultural lands.

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II. RELATED WORK

Reflectance Spectroscopy provides potentially useful alternative to traditional methods for soil elements analysis due to its convenience, accurate and rapidity. Spectroscopy in the visible (VIS, 400-700nm) and near-infrared (NIR, 700-2500 nm) ranges permits fast acquisition of soil information at quantitative and qualitative levels on the soil properties.

Guanghui Zheng et al, students of Nanjing University of Information Science & Technology, NUIST, Nanjing, China have done research on soil arsenic soil contamination. In this study they used the partial least squares (PLS) regression to find out the possibilities of reflectance spectroscopy in the VNIR ranges to predict the content of arsenic (As) in the soil samples. They compared PLS with OPLS [1].

Tiezhu Shi et al. from Resource and Environmental Science and Key Lab of GIS of Education ministry, Wuhan University, 430079 Wuhan, China They have found that to explore the feasibility and to investigate the mechanism for quickly monitoring arsenic (As) contamination in agricultural soils with the spectral reflectance of rice plants. Various data pre-treatment methods were applied to improve the prediction accuracy.

J. Kobza investigated the Problem of soil and plant pollution by heavy metals in Slovakia. The measured data on the main heavy elements have been obtained from a soil-monitoring grid in Slovakia, which consists of 318 agricultural sites. Analytical procedures of As, Cd, Pb, Cr, Ni, Zn, Cu (extracted by 2 mol/l HNO₃ and by 0.05 mol/l EDTA) also the total content of the described elements including Hg had been used for soil samples. Also the plants collected at the same sampling sites were analysed for their As Cd, Pb, Cr and Hg contents. On the basis of the obtained results it might be concluded that significant pollution was obtained only on 0.4% of the total soil cover in Slovakia [3].

Antoine Stevens et al. found that the temporal evolution in Soil Organic Carbon (SOC) content was often used in estimation of greenhouse emission fluxes and is a vital indicator of soil quality. Visible and Near Infrared Spectroscopy provides an option to chemical analysis process. The advantage of this technique include a reduction of the sampling processing time, an increase in the number of samples that may be analysed within time budget and time conditions and hence an improvement of the identification of small changes in SOC stocks for a given area [4].

H.M. Bartholomeus et al. has done research on 40 samples from nine different soil types, originating from several climate zones and a huge variety in SOC content (0.06–45.1%). Spectral measurements for all soil samples were performed in a controlled laboratory environment. They tested the performance of several spectral indices which have been developed to identify biochemical constituents (e.g., lignin, Cellulose) for their capacity to retrieve SOC, and compared it to PLS [5].

REN Hong-Yan et al. did a study for predicting soil heavy metal contaminations using laboratory spectral reflectance; this research information provided another tool for investigation of contaminated soil ecosystems by remote sensing. Conditions in laboratory might be more practicable than those in the field; therefore, spectral reflectance collected in laboratory were suitable for differentiating characteristic spectral wavebands used in the measuring models of As and Cu concentrations. so, the results could be validated and explored by further investigations because reflectance spectra collected under field condition are affected by natural soil surface [6].

Chang CW et al. found that Concentrations of Iron (Fe), As, and Cu in soil samples from the of Hunan Province fields near the Baoshan Mine, China, were analysed and soil spectral reflectance was measured with an ASD Field Spec FR Spectroradiometer under laboratory situation. Partial least square regression (PLSR) models were constructed for measuring soil metal concentrations [7].

Mark Cave et al. investigated the self-modelling mixture resolution of the raw NIR spectra has proved to be an efficient approach for extracting the useful information from a data matrix of spectra containing 4149 by 60 data points to a set of 5 coefficients by 60 samples. The predictive ability of the regression model is comparable with the continuity of the laboratory measurement of bio accessible As and would be fit for human health risk assessment purposes. For other soil types, particularly where the presence of As is due to anthropogenic inputs, the controlling factors on the bio accessibility of As are likely to be very different from the natural Jurassic ironstone soils [8].

M. Chen et al. did a study on cumulative probability distributions of As concentrations in seven major Florida soil types. They observed large distribution characteristic of As for each soil order Arsenic concentrations varied significantly among various types of soil in Florida. Generally, As concentrations reduced in the order of Histosols > Inceptisols > Mollisols > Ultisols[9].

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Shamsoddini, S. Raval et al. investigated the estimation of soil heavy metal contamination using spectroscopic method. In this study of samples from along stream adjacent to shafts of the derelict former Yerranderie silver-lead-zinc mines in the Blue Mountains National Park, NSW, Australia. The results of the chemical analysis showed that the derelict Yerranderie mine area impacts the soil of downstream areas. The soil is mainly contaminated by lead and arsenic. The results of this study show that these two heavy metals were estimated more accurately than the other heavy metals using spectroscopic data. Finally it was shown that while the first derivative of the reflectance data is the most suitable option for modeling the heavy metals, the models derived from the original reflectance data performed poorly [10].

Selige, T., Bohner et al. did a study on recent approaches to make digital soil maps based on geographical information systems shows that soils can be measured from other soils attributes at the same location or from soil and attributes of environment from neighboring locations (McBratney et al., 2003). Remote sensing data, especially for areas where the soil surface is temporarily or permanently exposed can be an important tool for gaining geographical information about soils [11].

Yong Hea et al. applied standard procedures for measuring soil properties are complex, time consuming. When requires more samples it becomes costlier. A rapid and economical soil analytical technique is needed, which will be useful for the precision farming. Visible-NIR spectroscopy is a rapid and non-destructive technique that matches diffusely reflected near infrared radiation with the chemical and physical properties of materials are used for assessing grain and soil qualities [12].

REN Hong-Yan et al. found that increasing heavy metals of trace amounts are affected by those spectrally active components of soil, which makes the spectrally featureless heavy metals and the spectrally active constituents correlated. The presented hypothesis of those heavy metal concentrations can be indirectly determined by soil reflectance spectra by showing the relationship between concentration of metal and other soil characteristics. Predictions of Hg, Cd and Zn have referred this hypothesis. Moreover, much attention was given to soil matter content and its spectral characteristics because soils varies in the organic matter content as well as ferric oxide concentration [13].

M.R. Malekil et al. investigated a reliable calibration model with the VIS and NIR spectroscopy method to measure the content phosphorus (P) in fresh soil as first step towards the creation of an automated variable rate fertilizer distributor. Phosphorus (P) is required for relatively more amounts by plants for root and seed development [14].

Irons, J.R et al. found that phosphorus is a difficult element as variable amounts can be fixed in the soil. Quantitative spectral analysis of soil with VIS-NIR reflectance spectroscopy requires statistical techniques to differentiate the response with attributes of soil from spectral features. Various methods are used to relate soil spectra to soil attributes. Partial least-squares regression is most common techniques for spectral prediction and calibration [15].

Henderson, T.L et al found that Organic Carbon (SOC) has been discovered as being one of the important C sinks in the global carbon cycle. The proper size of this sink and its distribution are hard to identify. Remote Sensing is a technique which is used for a better estimation of the amount of SOC [16].

HELEN TAYLOR et al. did a study on pollution causes many negative effects on soil quality. One of these effects is intake of the most important pollutants into the food chain and environment. The soil transfer into pollutants into the plants causes many physiological disorders. Plant uptake of pollutants from the soil is determined by pollutants distribution in the soil [17].

Bhosle Arjun B et al. has done research in Nanded city. They investigated number of physio-chemical parameters like pH, EC, organic matter, alkalinity, carbonate, chloride, calcium, magnesium, specific gravity, and moisture content was determined. In middle part of Nanded city soil depth is more. Because of it more houses are find cracks in these areas even they are newly constructed too. So main reason to find cracks to houses in this area is soil depth, after few time houses are get settled in this black cotton soils.

Godbole Mahendra T. investigated the Ni, Cr, and As is generally elevated in most localities, originating from geologic formation. The continuous higher intake Ni and Cr may cause toxic effects to the human health. The elevated concentrations of trace elements are combined effects of geogenic, sources as well as excessive use of chemical fertilizers. It is recommended to control anthropogenic activities adequately in order to minimize the pollution problems. Except Ni, Cr and As concentration. Overall groundwater quality is good for drinking and agricultural purposes [19].

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III. METHODOLOGY

Soil samples spectral reflectance was measured using a FieldSpec Pro FR spectrophotometer. The instrument measures spectra having a resolution of 1.4 nm and 2 nm and interpolated the data to produce 1-nm-spaced data. Reflectance spectra were gathered over the wavelength ranging from 350nm to 1335nm. Then several spectral processing techniques including first/second derivative reflectance spectra (F/SDR), inverse (1/R), inverse-log spectra (log(1/R)) and Band Depth were used. Then they achieved six spectral indices: Hamming, FDR, SDR, 1/R, log(1/R) and Band Depth. In this study they used the partial least squares regression to find out the possibilities of reflectance spectroscopy in the VNIR ranges to measure the content of arsenic (As) in the soil samples.

The Orthogonal projections to latent structures (OPLS) is a recent modification of the PLS method that will seek out variation in X that is not related to variation in Y and discard that part from the X-data, which will hopefully lead to better calibration models. OPLS may be the approach for continuous good measurement and interpretation of complex multivariate systems.

The field spectra of rice plants were measured during the booting stage. In between 10:00 and 14:00 the field spectral measurements were taken under cloudless or cloudy situation, using an ASD FieldSpec3 portable spectroradiometer. It has a spectral range of 350–2500 nm, and its interval of sampling is 1.4 in the 350–1000 nm range and 2 in the 1000–2500 nm range. The prediction accuracy strongly depends on the data pre-treatment methods applied to the reflectance spectra. In terms of RMSECV and AIC, the number factor of PLSR was 5, and from this first five principal components have given about 96.78% of the variation of the spectral data. Soil Arsenic Content measurement with NDSI. The NDSI values with 812 and 782 nm calculated from field spectra can show 46.6% of the variation of the soil As contents of soils in the calibration data set using a linear regression model [2].

The parameters used to evaluate the quality of the calibration and validation were the root mean square error of cross-validation and the root mean square error of prediction given by

$$\begin{aligned}
 \text{RMSECV} &= \sqrt{\frac{\sum (y_m - y_p)^2}{N_c}} \\
 \text{RMSEP} &= \sqrt{\frac{\sum (y_m - y_p)^2}{N_p}}
 \end{aligned}
 \tag{1}$$

Fig 1. Root mean square error of cross-validation and the root mean square error of prediction.

Where,

Y_m is the measured value.

Y_p is the predicted value from the PLSR model.

N_c is the number of samples in the calibration set.

N_p is the number of samples in validation set.

The best prediction model is shown by the lowest R.

IV. RESULT AND DISCUSSION

Guanghai Zheng found that the results from the laboratory analysis of soil As are observed that all the number of components used to calibrate is 1. Among the six indices, FDR gets the best result in the calibration, the Cumulative Y variance is 0.9140, the Cumulative cross-validation X-variance is 0.6030 and RMSEV is 1.0696. SDR and Hamming show good result. The result of Band Depth, log (1/R), and 1/R are worse. The RMSEP of FDR is similar to SDR and they have the biggest determination coefficients of regression line, which shows that the two indices have the best results of validation. The validation results of Band Depth, Hamming, 1/R and log.

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The single factor index was used to evaluate the risk of As. We found that the content of As in all the samples was beyond the local environmental background value. The average pollution index was 1.54.

Yiyun Chen et al. found in the study, the wavelengths centered near 540, 690, 730, 780, and 1170 nm of laboratory spectra at the leaves level were statistically identified as the important wavelengths for calculating the As contents in agricultural soils. All identified important wavelengths were within the region of 350–1200 nm, which shows that the spectral region of 1201–2500 nm might be uninformative for predicting the As contents in soils.

Patode Hari S et al. found that Chronic inorganic arsenic exposure is known to be associated with bad health effects on several systems of the body, but is most known for causing specific types of skin lesions and increased risks of cancer of the lung and skin ingesting contaminated soil or foods (predominantly via hand-to-mouth activity. Groundwater can be affected with arsenic from natural sources of arsenic also with mining and smelting operations (U.S. EPA, Toxicity and Exposure Assessment for Children's Health). The arsenic in study area ranging from 0.2 mg/l to 0.03mg/l and, average is 0.22 mg/l. All the water samples of study area are below the WHO standards [18].

V. CONCLUSION

The excess content of arsenic causes various effects on human health and also soil infertility which causes crop damage. Partial Least Square is mostly used method for predicting arsenic in soil. The objective of this study is to determine content of arsenic through reflectance spectroscopy. Reflectance spectroscopy in the VNIR ranges uses to predict the content of arsenic in the soil samples. It is concluded that this study gives how to increase fertility of soil.

ACKNOWLEDGEMENT

This work is supported by Department of Science and Technology under the Funds for Infrastructure under Science and Technology (DST-FIST) with sanction no. SR/FST/ETI-340/2013 to Department of Computer Science and Information Technology, Dr. Babasaheb Ambedkar Marathwada University, Aurangabad, Maharashtra, India. The authors would like to thank Department and University Authorities for providing the infrastructure and necessary support for carrying out the research.

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