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Prediction of soil physicochemical properties by Visible and Near-Infrared Diffuse Reflectance Spectroscopy using Partial Least Square Regression

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Abstract:

Organics, chemical fertilizers play a crucial role for improving crop yield and soil properties. The impact of fertilizers on soil properties intensively for banana and cotton cropping system with organic; chemical and mixed (organic + chemical) treatments assessed for Raver tehsil of Jalgaon district. Remote sensing techniques using visible near-infrared diffuse reflectance spectroscopy has been demonstrated to be a fast tool for estimating a large number of physicochemical soil properties, and effective features extracted from spectra are crucial to correlating with these properties. The FieldSpec4 spectroradiometer was used for spectral data acquisition then Sand, silt, clay, SOM, moisture, pH, carbon, nitrogen, phosphorous, potash soil physical and chemical properties are assessed from spectral data. The PLSR modeling approach was evaluated in the present study to achieve spatial prediction of soil properties. Results of Partial Least Square Regression modeling showed significant prediction of physicochemical soil properties with regression coefficient values (R^2) showed highly correlation. The results indicated that PLSR modeling were suited for soil physicochemical properties prediction of spectral data. This techniques is best suited for large scale of remote sensing spectral data.

Keywords: **soil properties, fertilizers, spectroradiometer, PLSR.**

Introduction:

Soils as a significant ingredient of terrestrial ecosystems are extremely important. Soil physicochemical properties are the basic indicators for soil productivity, which is powerfully linked to agricultural output [1]. The soil assessment important for real long-term soil degradation due to poor agricultural practices, heavy use of fertilizers and erosion on agriculture land [2]. The traditional soil assessment methods are manual and time consuming. The quantitative assessment of soil properties using visible near-infrared shortwave infrared (Vis-NIR-SWIR) spectroscopy has been demonstrated as a fast and non-destructive method [3, 8]. The technique is mainly used in the laboratory, where soil samples are prepared and measured under controlled conditions, and it can be considered as an alternative to traditional analytical techniques [4-6]. The determination of the spatial extent of soil resources is difficult task at a specific site [7, 9]. There is a need to develop a remote sensing based approach for spectral determination of soil properties. Several researcher has made attempt to aces and predict soil properties using hyper spectral imaging and non-imaging data. In this present study attempt has been made to analyze spectral data to develop an approach for the physicochemical soil properties assessment. The PLSR method is used to model a possible linear relationship between measured soils properties and predicted soil properties for prediction of soil physicochemical properties. The general idea of PLSR is to extract the orthogonal or latent predictor variables, accounting for as much of the variation of the dependent variable(s) [18]. In this study, PLSR method used to model correlation between measured soil properties and predicted soil physicochemical properties. Measured soil properties which was selected from quantitative data 70 % data and with remaining 30 % data for sand, silt, clay, moisture, SOM, pH, carbon, nitrogen, phosphorous, potash parameters were used for the PLSR analysis. The every scale of study field, data used to build the PLSR models were randomly divided into calibration and prediction sets. The PLSR models were developed independently for each soil properties. The results shows that among all observed soil parameter sand, silt, clay, moisture, SOM, pH, carbon, nitrogen, phosphorous, potash predicted accurately based on PLSR models developed for quantitative data. The consequences were useful for soil contamination, soil degradation, environmental monitoring and precision agriculture [23]. Results showed that the prediction accuracy based on lab spectroscopy, Understanding variability of soil attributes allows the improvement of environmental and agricultural management as well as a more effective usage of resources.

2. Materials and Methods:

Soil samples are collected from Raver tehsil of Jalgaon district (Study area) where Organic, Chemical and Mixed fertilizers treatments used for banana and cotton crops sites in two different season in year 2018 with GPS locations and create a dataset as DS-I. The soil samples are collected as per the guideline of soil survey and soil testing, Agriculture department Maharashtra Government. In pre-monsoon (May) season soil samples were collected. As well as, in post monsoon (First week of November) season soil samples were collected where different fertilizers treatment used for different crops. Collected soil samples are classified according to season, fertilizers treatment and crop wise like Pre monsoon Organic Cotton (PROC), Post monsoon Organic Cotton (POOC), Pre monsoon Mixed Cotton (PRMC), Post monsoon Mixed Cotton (POMC), Pre monsoon Organic Banana (PROB), Pre monsoon Mixed banana (PRMB), Pre monsoon Chemical Banana (PRCB), Post monsoon Organic Banana (POOB), Post monsoon Mixed Banana (POMB), Post monsoon Chemical Banana (POCB). Also same soil samples are collected in the year 2019 pre monsoon and post monsoon and create dataset as DS-II. The appropriate soil sampling and preparation of soil samples methods are used for data collection [10-14].

2.1. Data acquisition:

Data acquisition perform using ASD FieldSpec4 Spectroradiometer (Analytical Spectral Devices Inc., Boulder, Colorado, USA) NIR reflectance spectroscopy performed in under controlled lab condition, it relatively simple, non-destructive, reliable, inexpensive, fast, and accurate method for characterizing soil sample. The required set up were used for data acquisition [15-18] in Multispectral Research lab, Department of Computer Science & Information Technology, Dr. Babasaheb Ambedkar Marathwada University, Aurangabad with the ASD FieldSpec4 sensor. There are 10 spectral signature are acquired for each samples.

2.2. Data processing:

The acquired 10 spectral signatures for each samples are processed by applying mean and generate one spectral signature for each sample [19-20]. The different fertilizers and crop wise mean data were processed and it represented in figure 1. In this representation fertilizer and crop wise difference clearly saw. Then convert the mean spectral data into numeric format for further process.

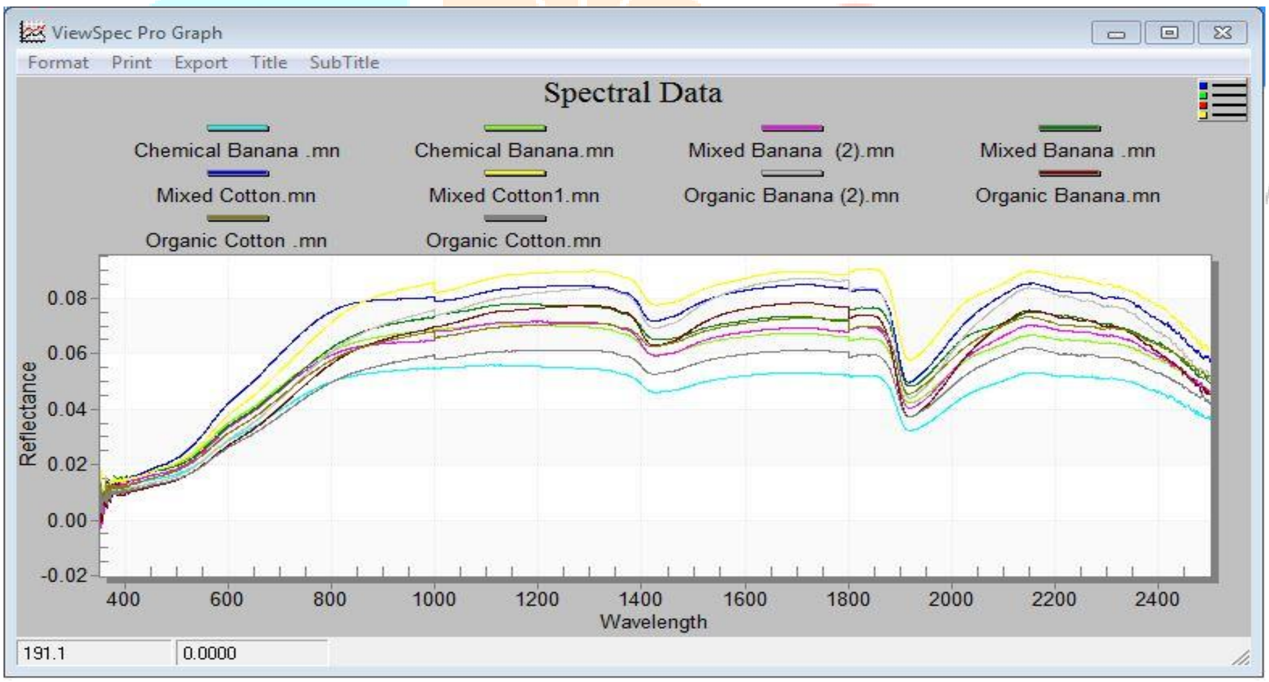


Figure 1. Category wise mean of acquired spectral data

The spectral mean data converted in numeric format using ViewSpecPro software. Numeric data were opened in Microsoft Excel and process the by applying statistical mean methods for quantitative analysis of soil properties on the respective absorption wavelength range [19-20,22].

3. Results and Discussion:

The spectral data acquisition perform using ASD FieldSpec4 Spectroradiometer and process the spectral data by applying statistical methods for quantitative analysis. Table 1 showing the representation of DS-I and DS-II datasets with quantitative values of physicochemical properties. The partial least square regression were applied on quantitative data for development of physicochemical soil properties prediction modeling.

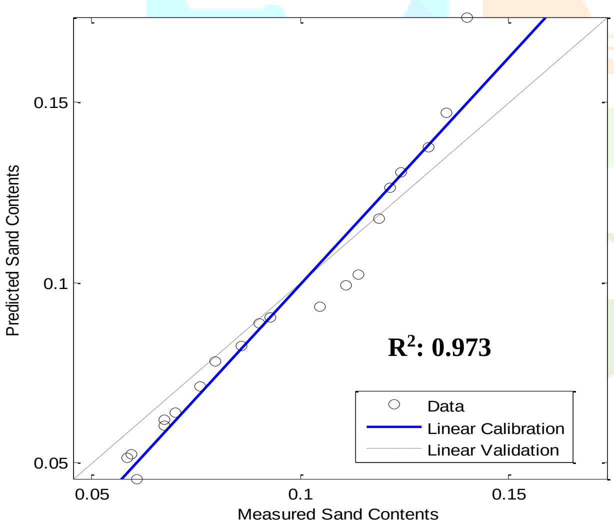
Table 1: Quantitative analysis of spectral data

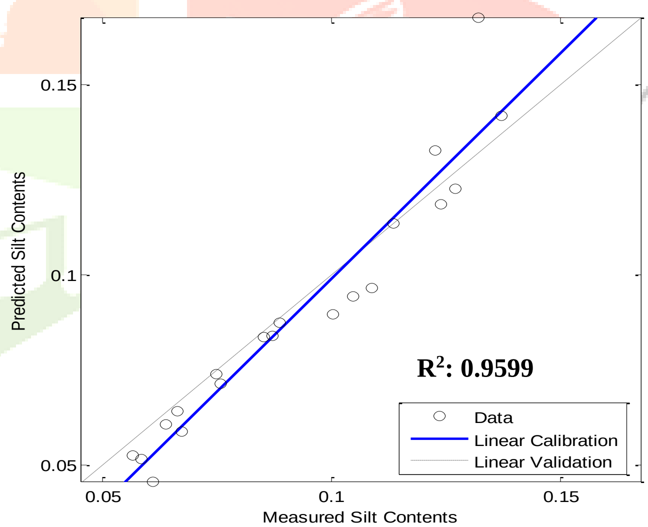
Database	DS-I & DS-II										
	Soil sample	**Sand**	**Silt**	**Clay**	**SOM**	**Moisture**	**pH**	**Carbon**	**Nitrogen**	**Phosphorus**	**Potash**
DS-I	**POOC**	0.061	0.061	0.063	0.038	0.062	0.061	0.067	0.067	0.066	0.065
	PROC	0.059	0.059	0.061	0.039	0.060	0.058	0.064	0.064	0.063	0.063
	POOB	0.060	0.057	0.059	0.057	0.056	0.050	0.061	0.057	0.058	0.053
	PROB	0.067	0.064	0.067	0.064	0.066	0.057	0.069	0.065	0.066	0.059
	POMC	0.068	0.068	0.070	0.039	0.069	0.066	0.074	0.077	0.072	0.074
	PRMC	0.070	0.066	0.069	0.067	0.068	0.059	0.071	0.067	0.068	0.062
	POMB	0.076	0.076	0.079	0.047	0.079	0.075	0.083	0.085	0.082	0.082
	PRMB	0.080	0.075	0.079	0.076	0.084	0.064	0.081	0.075	0.077	0.069
	POCB	0.086	0.087	0.088	0.086	0.085	0.079	0.088	0.090	0.087	0.080
	PRCB	0.090	0.085	0.090	0.086	0.077	0.074	0.092	0.085	0.088	0.079
	POOC	0.093	0.089	0.093	0.089	0.090	0.079	0.095	0.089	0.091	0.082
	PROC	0.105	0.101	0.105	0.102	0.099	0.088	0.105	0.106	0.104	0.093
	POOB	0.111	0.105	0.109	0.106	0.105	0.091	0.112	0.106	0.107	0.097
	PROB	0.114	0.109	0.115	0.109	0.107	0.097	0.116	0.109	0.113	0.101
	POMC	0.119	0.114	0.119	0.114	0.117	0.101	0.121	0.113	0.117	0.105
	PRMC	0.121	0.124	0.128	0.123	0.120	0.104	0.128	0.130	0.126	0.112
	POMB	0.124	0.127	0.131	0.126	0.123	0.107	0.130	0.131	0.129	0.114
	PRMB	0.131	0.123	0.131	0.124	0.131	0.105	0.133	0.122	0.129	0.113
	POCB	0.135	0.137	0.142	0.137	0.134	0.121	0.141	0.143	0.140	0.126
	PRCB	0.140	0.132	0.141	0.135	0.130	0.117	0.140	0.140	0.139	0.123
DS-II	**POOC**	0.046	0.046	0.047	0.034	0.046	0.045	0.049	0.049	0.048	0.048
	PROC	0.051	0.051	0.053	0.033	0.052	0.051	0.057	0.057	0.056	0.055
	POOB	0.052	0.052	0.054	0.038	0.053	0.052	0.056	0.057	0.055	0.055
	PROB	0.061	0.061	0.063	0.036	0.062	0.060	0.067	0.068	0.065	0.066
	POMC	0.062	0.059	0.062	0.059	0.063	0.052	0.063	0.059	0.061	0.055
	PRMC	0.064	0.064	0.066	0.042	0.066	0.063	0.070	0.071	0.068	0.068
	POMB	0.071	0.071	0.074	0.049	0.072	0.071	0.078	0.078	0.076	0.076
	PRMB	0.078	0.074	0.077	0.074	0.074	0.065	0.079	0.075	0.076	0.069
	POCB	0.083	0.084	0.086	0.082	0.081	0.075	0.085	0.087	0.084	0.077
	PRCB	0.089	0.084	0.088	0.084	0.083	0.073	0.090	0.084	0.086	0.078
	POOC	0.090	0.087	0.091	0.088	0.086	0.079	0.090	0.092	0.090	0.081
	PROC	0.093	0.090	0.094	0.090	0.088	0.081	0.093	0.094	0.092	0.083
	POOB	0.099	0.094	0.100	0.094	0.102	0.083	0.101	0.094	0.098	0.087
	PROB	0.102	0.096	0.103	0.098	0.093	0.084	0.105	0.095	0.101	0.089
	POMC	0.118	0.113	0.118	0.114	0.121	0.099	0.120	0.111	0.117	0.105
	PRMC	0.126	0.119	0.131	0.124	0.131	0.105	0.133	0.122	0.129	0.113

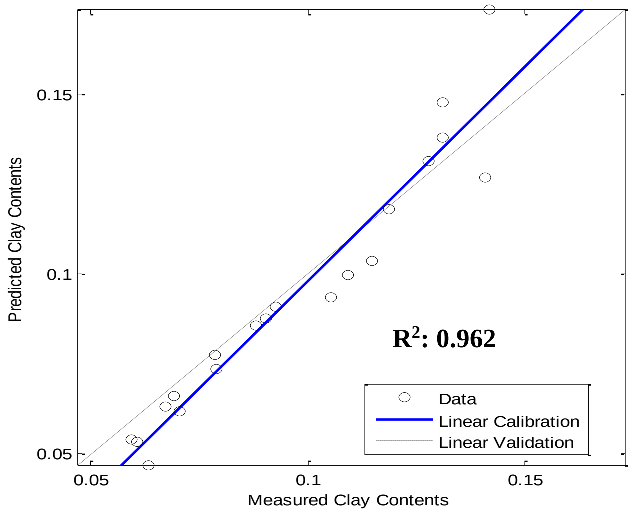
	POMB	0.131	0.123	0.138	0.133	0.142	0.119	0.140	0.131	0.136	0.123
	PRMB	0.137	0.133	0.147	0.143	0.147	0.126	0.150	0.140	0.146	0.131
	POCB	0.147	0.142	0.173	0.168	0.138	0.149	0.177	0.166	0.172	0.155
	PRCB	0.174	0.167	0.127	0.121	0.117	0.100	0.126	0.127	0.125	0.109

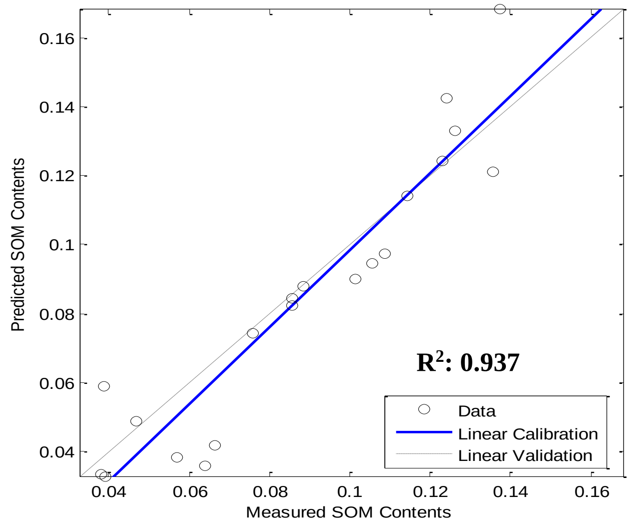
3.1. Prediction of soil properties using PLSR modeling:

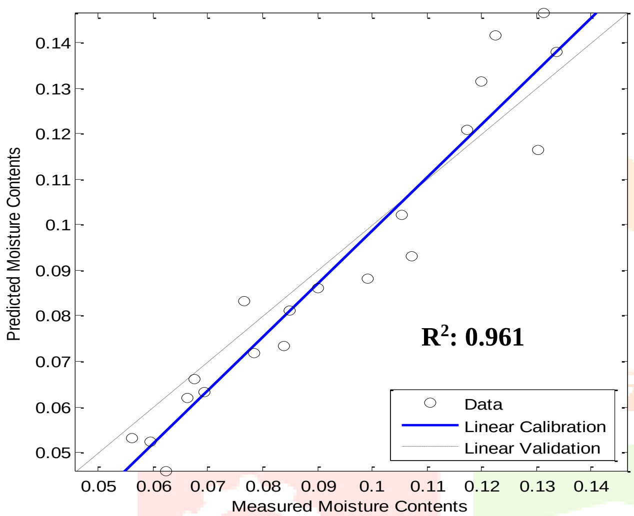
The PLSR method specifies linear relationship between mesured and predictor variables. PLSR model is developed on the basis of calibration and validation also called as training and testing. each category of collected soil samples data is used to build the PLSR models is divided into calibration and validation sets. 70% data were used for calibration and 30% data were used for validation. The prediction models were developed for each independent soil properties. the result shows that the among soil parameters sand, silt, clay, SOM, moisture, pH, carbon, Nitrogen, Phosphorous, Potash prediction can be made accurately based on PLSR model developed from collected soil samples. The prediction of sand, silt, clay, SOM, moisture, pH, carbon, Nitrogen, Phosphorous, Potash soil parameters considerd as best because the regression coefficient values (R^2) of soil properties are highest.






Predicted Clay Contents
Measured Clay Contents
R²: 0.962
Data
Linear Calibration
Linear Validation


Predicted SOM Contents
Measured SOM Contents
R²: 0.937
Data
Linear Calibration
Linear Validation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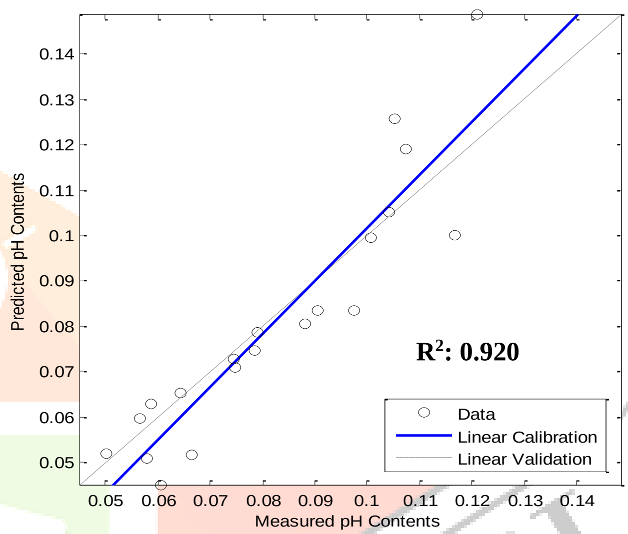
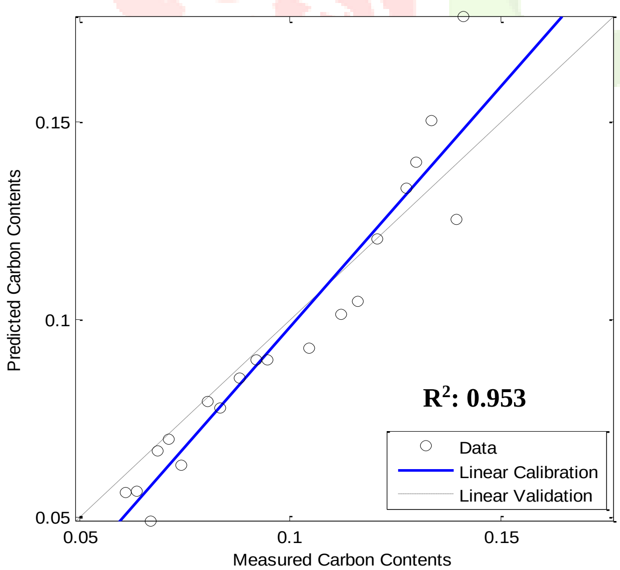
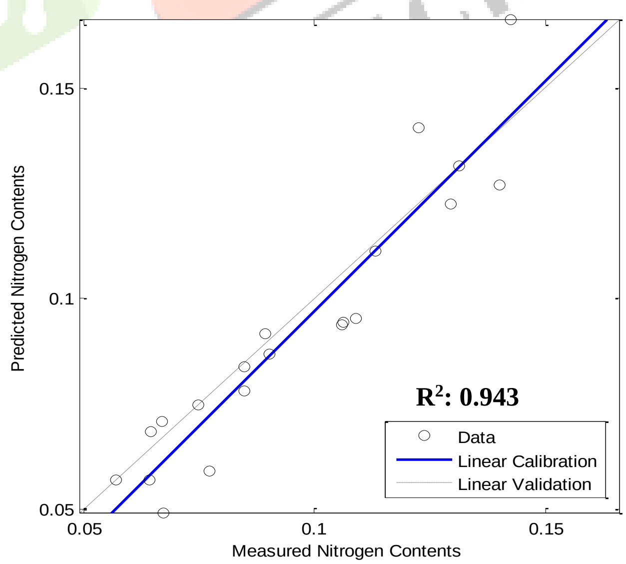
Measured Moisture Contents
R²: 0.961
Data
Linear Calibration
Linear Validation


Predicted pH Contents
Measured pH Contents
R²: 0.920
Data
Linear Calibration
Linear Validation


Predicted Carbon Contents
Measured Carbon Contents
R²: 0.953
Data
Linear Calibration
Linear Validation


Predicted Nitrogen Contents
Measured Nitrogen Contents
R²: 0.943
Data
Linear Calibration
Linear Validation

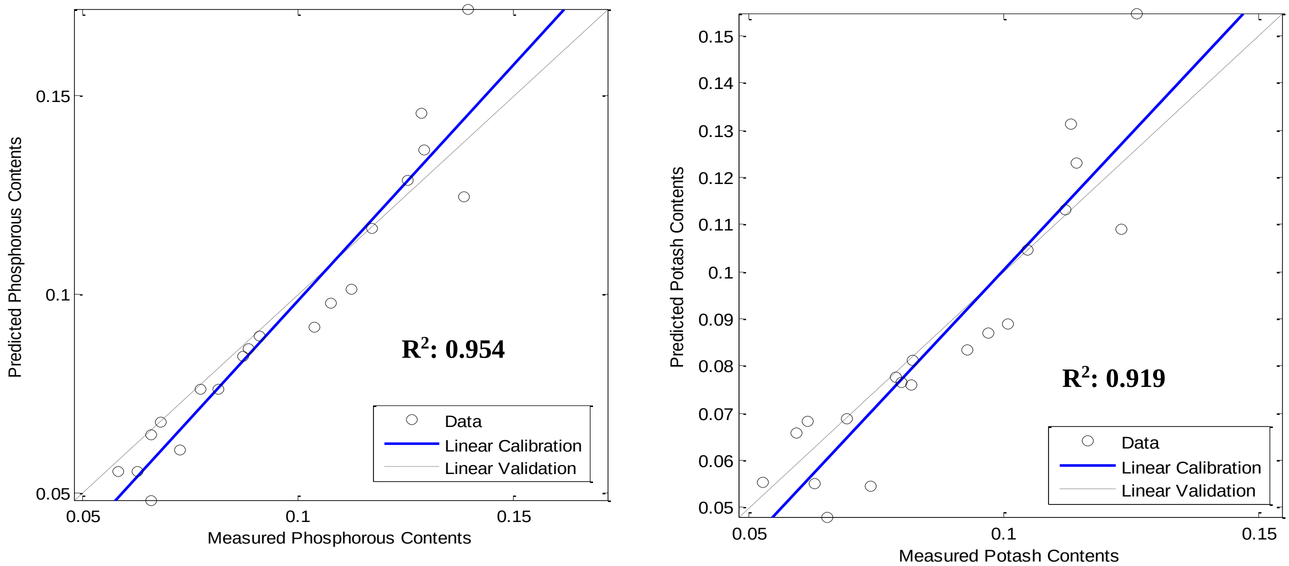


Figure 1. PLSR modeling with calibration and validation for each soil properties

The resuls showed (Figure:1) R^2 values of measured values vs. predicted values of sand, silt, clay, SOM, moisture, pH, carbon, Nitrogen, Phosphorous, Potash were 0.973, 0.9599, 0.962, 0.937, 0.961, 0.920,0.953, 0.943, 0.954, 0.919 respectively. Calibration and validation using measured value vs. predicted values are represented in figure 1 for each soil properties. Linear calibrations is represented with continuous straight line and linear validation is represented with dotted straight line for each soil propeties. The PLSR model accurately predict the soil properties on the basis of linearly calibration and validation. It is used for prediction of soil properties on the basis of measured soil properties.

4. Conclusion:

The soil properties assessment using visible near-infrared shortwave infrared (Vis-NIR-SWIR) spectroscopy has been demonstrated as a fast and non-destructive method and it can be an alternative to traditional analytical techniques. The spectroradiometer data provides the large range of spectral representation of soil samples and required plant growth soil properties can be analyzed through spectral data. The quantitative analysis provides the availability of soil properties which are extracted from specific absorption spectral rage. The PLSR modeling used to prediction and correlation between measured and predicted soil physicochemical properties. The PLSR models were developed independently for each soil properties. The results shows that among all measured soil parameter sand, silt, clay, moisture, SOM, pH, carbon, nitrogen, phosphorous, potash predicted accurately based on PLSR models developed from quantitative data. The predictions of sand, silt, clay, moisture, SOM, pH, carbon, nitrogen, phosphorous, potash soil parameters can be considered good, regression coefficient values (R^2) of such soil properties showed highly correlation. The PLSR modeling is useful for prediction of soil properties assessment and it perform fast execution.

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