# Assessment of micronutrients from soil using hyperspectral data

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***Abstract***— Soil physiochemical attributes detection is difficult and crucial part in soil science, soil attributes are varied in spatially and temporally with the complexity of nature. Soil physiochemical laboratory analysis method is very time consuming and difficult. However, this paper introduced hyperspectral reflectance spectroscopy and studied within visible (350-700nm) and near infrared (700-2500nm). Imagery spectroscopy (400-1000nm) is used to categories the spatial characteristics of soil contents. 30 soil samples were collected from the vegetable farm near Tahsil, District Jalna region Maharashtra. Spectra of soil samples acquired using Analytical Spectral Device (ASD) Field spec 4 spectroradiometer. Imagery data were collected from PIKA L spectroscopy. The spectra data were preprocessed and given input to the regression model. A partial least squares regression PLSR model was used for prediction of soil attributes from spectroscopy data. The correlation result ($R^2$) for Zinc, Iron, Copper, Magnesium are as 0.903, 0.829, 0.948, 0.952 with RMSE 0.036, 0.0037, 0.028, 0.018, whereas for as imagery part of spectroscopy used the index NIODI for fe and predicted result as Fe: 0.09848 respectively.

*Index Terms*- Soil attribute, Imagery Spectroscopy PIKA L, ASD Field Spect 4, PLSR partial least squares regression

## I. INTRODUCTION

Agriculture management systems are dependent on demands to control the expenses of production and to increase productivity. To obtain a better return from inputs in agriculture, numerous analyses are needed so that those inputs can be applied where they best fill their purpose. Most of the agricultural and environmental planning requires soil analysis. Furthermore, better practical analysis methods for soil properties are required to improve quantitative assessments of land management problems [1]. However, soils are more varied and dynamic in nature than air and water.

In addition, the structure, study and processes of soils are also complicated for both spatially and temporally. The chemical laboratory analyses are made to detect the soil chemical and physical attributes using hazardous solutions. However, these laboratory methods are time-consuming, expensive. Consequently, there is a universal need to develop speedy and less expensive methods to detect the soil micronutrient [2].

Hyperspectral remote sensing provides spectral information and proposes a potential method for estimating of soil properties. Hyperspectral techniques are more rapid and low prize, which can also eliminate the preparations and chemical reagents as compared to traditional laboratory methods [3]. VIS-NIRS technology has the potential to detect fine-scale spatial variability of soil. It should be needed to shift perspective, a transition from standard soil testing approach to the adoption of VIS-NIRS method for precision agriculture need [4]. Whereas Vis/Nir is being considered as a possible alternative for conventional chemical laboratory method, it is efficient when a large number of samples are required for analysis. Soil has weak composition and vibrations due to stretching of OH, NH, CH group which included in NIR (700-2500nm) and transition of bond in VIS (400-700nm) bands of spectral information [5]. The objective of this work was to investigate the usefulness of VIS-NIRS in determining various soil chemical properties (Zn, Fe, Cu, Mg, PH, moisture) in topsoil (20 cm) soil sampling from farm field. With that aim in mind, results from evaluation model in relation to predicted sample localization and soil micronutrients.

## II. RELATED STUDY

Hyperspectral imaging systems can be determined either in reflectance or transmittance modes. To acquire images or reflectance thin sample sizes are usually used to allow light to travel through the sample. Hyperspectral imaging systems provide hyperspectral images include numerous spatial image planes of the same object at different wavelengths. The resulting hyperspectral image were acquired through the overlaid of the spatial images collected by the hyperspectral sensors creating a three-dimensional data cube and also reflectance spectra from fieldspec 4A spectroradiometer [6]. More work has been done using hyperian remote sensing for soil but with spectroradiometer had a little contribution for soil content estimation as per the following study:

As per the study [6] a review of the recent developments in hyperspectral imaging systems and applications in food and food products is provided. This paper highlights the optical fundamentals of hyperspectral imaging and the most recent advances in the configurations and applications of hyperspectral imaging in food quality and safety control. There are many foods and fruits quality analyses by different analytical methods by using image processing pca, lda and threshold of such resulting values differentiate the mealiness of apple which was determined using VIS/NIR hyperspectral imaging. A classification accuracy of 82.5% was obtained using LLE algorithm-assisted SVM models. With the further work hyperspectral imaging of soil can be used for classification of soil types and estimation of total nitrogen content.

Jia, Shengyao, et al. author has stated in his research about classification of soil. Total 183 soil samples from shangyu city from china were collected, by using near-infrared hyperspectral spectroscopy with wavelength 879-1734nm collected soil reflectance. The soil samples classified to three major soil types including paddy soil, red soil and seashore saline soil. Further to select significant wavelengths from spectrum the successive projection algorithm (SPA) was used. The support vector machine and partial least square regression (PLSR) algorithm were used for classification and prediction model. The combine dataset of effective wavelength and classification for textured feature accuracy results as 91.8% [7].

According to the study [8] highlights the advantages of Remote Sensing (RS) and Geographic Information System (GIS) techniques were used for the land use/land cover mapping for Aurangabad region of Maharashtra, India. Cloud free IRS-Resourcesat-1 LISS-III data were used for further classification on training set for supervised classification. ENVI 4.4 image analysis tool and Arc GIS10 software were used for data processing and analysis. Maximum Likelihood, Mahalanobis distance, minimum distance and parallelepiped classifiers were performed for LULC classification in this study. It is observed that maximum area was covered by barren land, agricultural area (with crops and without crops), hilly area, built-up area and water bodies' etc respectively. The result of the classifications suggests that each used and covered type were best classified by the Maximum likelihood classification technique.

## III. Materials and Methods

Spectral analysis of soil using visible and infrared reflectance spectroscopy requires statistical techniques to describe the response of soil attributes from spectral characteristics.

### 3.1 Study site and soil sampling

Surface soil samples (0–20cm) were collected from a 30km$^2$ agricultural fields in Jalna, district Maharashtra, located 75°87'38.0227"N latitude and 19°84'22.7844" E longitude. The soil in the field consisted of mainly black loamy sandy soil. The site was with clear climate with temperature 31° to 33°. The samples collected from surface were dried and sieved and collected air tight bag with clear climate.

### 3.2 Spectral Analysis:

Field-Spec 4 spectrometer (VIS-NIR) (Analytical Spectral Devices, Inc.) was used for spectral data collection; measurements were taken with the bare fiber (FOV of 8°) at a distance of 15 cm above the soil samples and were directly converted to reflectance using a spectral on a panel as a reference [9]. Soil reflectance spectra were measured for each soil sample using an ASD field spectrometer, at wavelengths from 350 nm to 2500 nm with a spectral sampling interval of 1.4 nm. The method was used to perform the spectral measurements. Dish 20 cm in diameter and 1.5 cm in depth were overfilled with soil, were illuminated with tungsten quartz halogen filament lamps in housings with aluminium reflectors. The lamp was set as 60° of Zenith angle at a distance of 45cm above the soil sample. The reflected light was collected in 1-nm bandwidths between 0.35-2.5 μm [10].

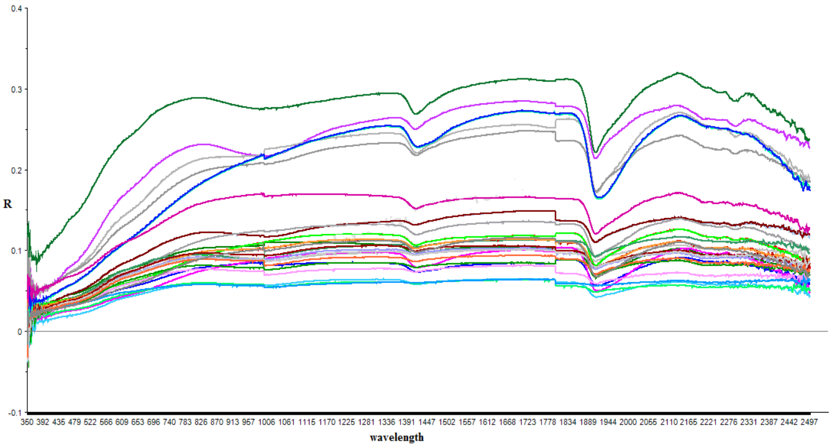



Figure.1 Soil spectra

In this study used Resonance hyperspectral imaging spectrometer with the spectral range 400-1000nm with the spectral channels 281 spectra resolution 2.1nm and pixel size is 5.86 um and with controlled quartz halogen lights had 12- inch travel linear scanning stage and tower height 81 cm for image camera mounting. Scanning max travel distance is 89 cm. By using this device scanned the image of soil with distance 50 cm of camera with time 2.1 sec scanning under the halogen light and collected hypercube of the soil image [11].

### 3.3 Preprocessing

In order to reduce the spectral data affected by spectral variation and sample texture, spectral data were analysed by using pre-processing method such as First Order Derivative (FD). It is showed that with FD transform method had the best effect with study of [12], [13], [14], [15], [16] menuscript. Preprocessing is carried out using software unscramble 10X, and carried further analysis by using python 3.6

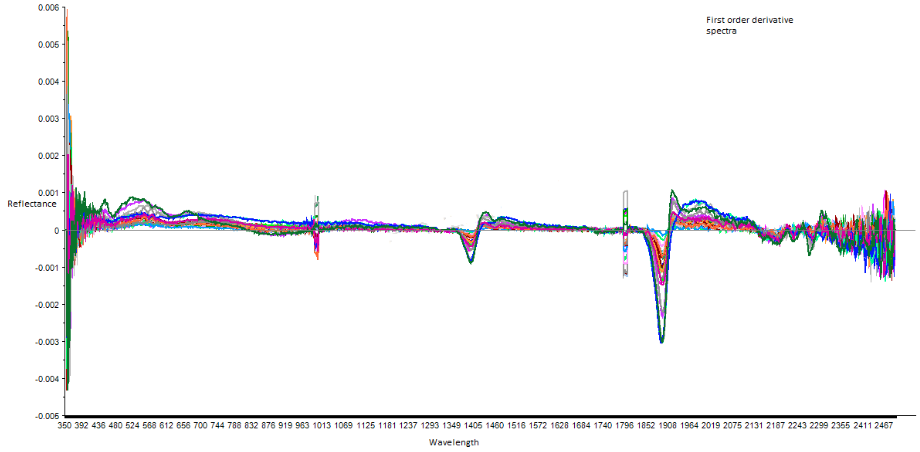



Figure.2 soil spectra for first derivative

### 3.4 Partial least-squares regression (PLSR)

The plsr regression method was proposed from multiple linear regression that reduce spectral data by calculating spectral collinear variables to non correlated latent variables. This regression algorithm mostly used for soil feature analysis. The aim of PLS regression algorithm is to make a linear model from X (mean of observed variables) and Y (mean of response variable) [12],[15].

Firstly, X and Y estimated from feature vectors in the form of following equation (1) and (2)

Y =UQ + F…….Eq. no. (1)
X =TP +E……..Eq.no.. (2)

Here, *U* and *T* are the score of matrices, *Q* and *P* are the loading matrices, and *F* and *E* are the residue matrices. The results are estimated in terms of correlation coefficient $R^2$ and RMSE. Whereas SSE is sum of square of error and SST total sum of square is sum of error and regression

$$R^2 = \frac{SSE}{SST} = \frac{SSE}{SSE + SSR}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (\tilde{y} - y)^2}{n}} \quad \text{……eq.no.. (3)}$$

$\tilde{y}$ is predicted y is observed.

Indices used for moisture water band that is shortwave water stress indices [17].

Eq.no.4

$$\frac{\mathrm{NIR}\lambda 908 - \mathrm{SWIR}\lambda 1900}{\mathrm{NIR}\lambda 908 + \mathrm{SWIR}\lambda 1900}$$

NIODI Index is used to determine the Fe using absorption feature of hematite is near 880nm and goethite 920nm and derived normalized iron oxide difference index (NIODI), this provides an objective for physical based presence of iron in soil.

Eq.no.5

$$NIODI = \frac{D_{920} - D_{880}}{D_{880} + D_{920}}$$

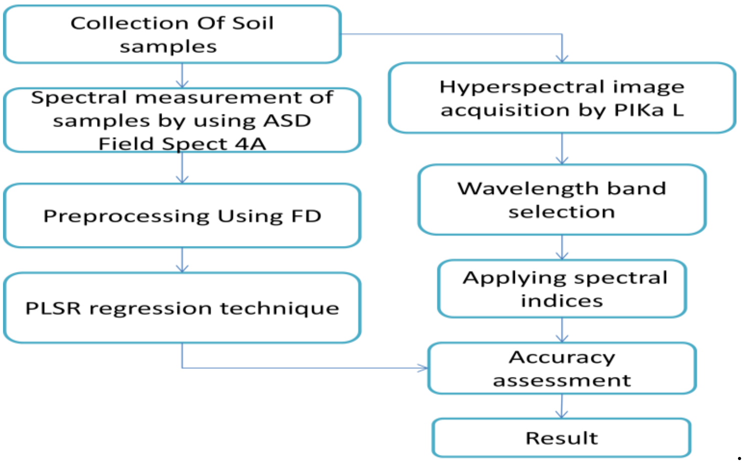



Figure.3. Methodology Flow Diagram

### 3.5 Hyperspectral Data Extraction and processing

Hyperspectral of 30 soil samples collected from Field Spect 4 of range 350-2500nm with fov 8° collected spectra of 30 soil samples show fig no1. As from figure no.3 in the first phase of methodology spectra data averaged to mean of 30 samples of soil. Firstly for the calibration and validation of soil samples divided in 1:2 part of soil. Transform method used such as First derivative at the second phase and applied machine learning algorithm PLSR regression method used for estimation of respective contents such as Zn, Fe, Cu, Mg, and moisture respectively. The plsr model accuracies for soil nutrients were determined by using correlation coefficient ($R^2$) and root mean square error (RMSE) [12] [13] as results are shown in below table no2.

For each soil samples hyperspectral image collected by PIKA L hyperspectral spectroradiometer, the region that covered the base cover of soil was selected as the region of interest. At a second phase of a methodology by using hyperspectral band image data used for estimation of soil contents. Firstly selecting particular wavelengths band image, afterward applying Band math method which calculate index for original raw image, applied index notices the presence of soil nutrients which are present within 400-1000nm.

## IV. RESULT AND DISCUSSION

Chemical laboratory test methods the results were estimated for soil contents which were depends on chemical method Diethylenetriamine penta acetic acid (DTPA) used for extraction. Soil samples have been evaluated values for content as Zn 0.138mg/l which can ranges above and below 0.138. Similarly for the other contents such as Fe 0.139mg/l, Cu with 0.137mg/l and with Mg 0.0845mg/l

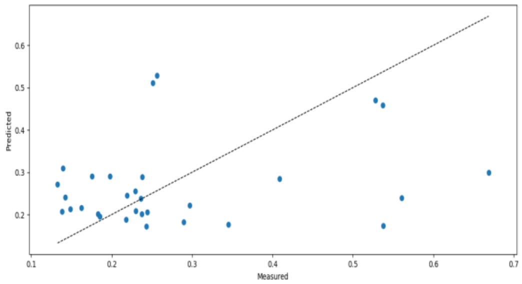
Table no.1

| Mg/l | Min | Max | Mean | Standard deviation |
|---|---|---|---|---|
| Zn | 0.138 | 0.193 | 0.289 | 0.1441 |
| Fe | 0.139 | 0.668 | 0.288 | 0.1469 |
| Cu | 0.132 | 0.649 | 0.286 | 0.1479 |
| Mg | 0.084 | 0.389 | 0.173 | 0.0887 |

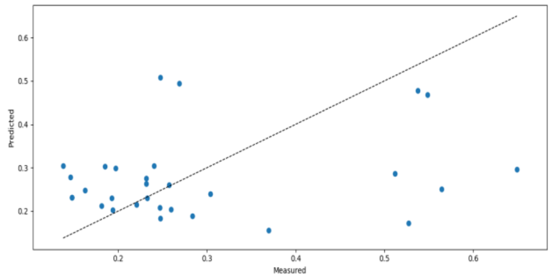
Spectral feature selected wavelengths with particular reflectance features which were calibrated by PLSR method for Zn, Fe, Mg, Cu with band as per the study of research manuscript [19],[20],[21],[22],[23],[24]. The spectral features wavelength correlated using pearson coefficient particularly for Fe 960nm, 725nm, Zn 985nm, 1185nm, Cu 990nm, 1447nm and for Mg 1416, 1945. After applying PLSR regression results are estimated with prediction accuracies using correlation coefficient ($R^2$) and root mean square error (RMSE) as per shown in Table no2.

Table no.2 prediction result on raw dataset

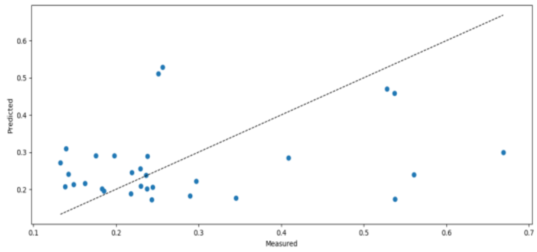
| | Training | | Testing | |
|---|---|---|---|---|
| | $R^2$ | RMSE | $R^2$ | RMSE |
| Zn | 0.754 | 0.069 | 0.403 | 0.105 |
| Cu | 0.602 | 0.05 | 0.90 | 0.076 |
| Mg | 0.952 | 0.018 | 0.862 | 0.026 |
| Fe | 0.565 | 0.075 | 0.923 | 0.045 |
| moisture | 0.55 | 0.032 | 0.873 | 0.05 |



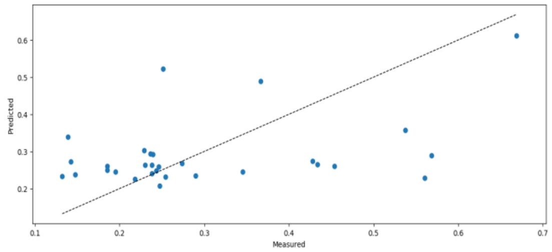

(a)



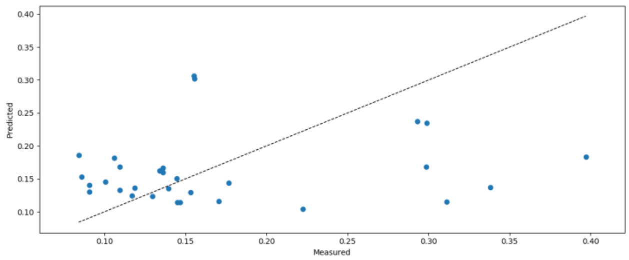

(b)




(c)



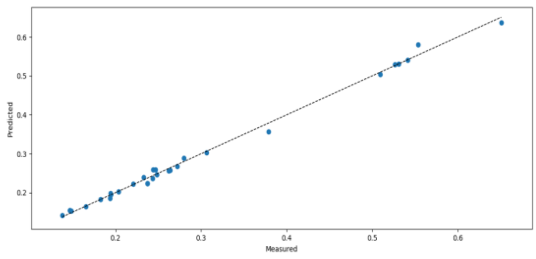

(d)



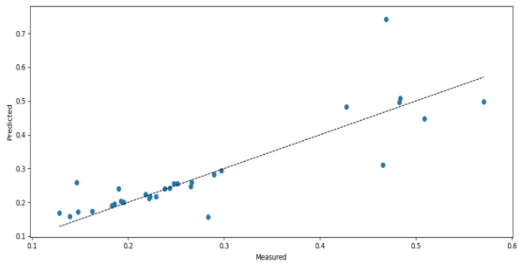

(e)

Figure. 4 Scatter plot before preprocessing for Fig.(a)Zn, Fig.(b)Cu, Fig.(c)Fe, Fig.(d)Mg, (e)moisture using raw dataset

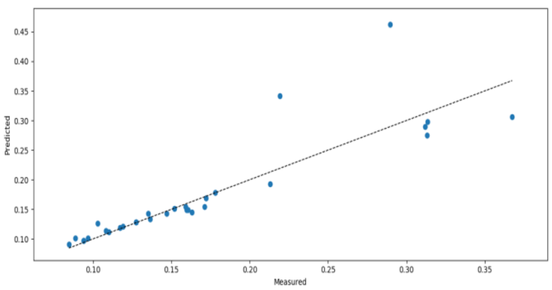
After applying PLSR method prediction result for Zn, Fe, Mg, and Cu were obtained on raw dataset described in table.no2. The plsr method was evaluated using cross validation $R^2$ and RMSE for content. As table no.2 described with satisfactory accuracy on raw dataset for Zn $R^2$= 0.75 and RMSE 0.069, for Cu $R^2$=0.6002 and RMSE 0.05, for Mg $R^2$= 0.952 RMSE 0.018 for Fe $R^2$= 0.565 RMSE 0.075. In Fig.4. Illustrate the scatter plot of measured values and prediction values of all soil properties derived from plsr model before its pretreatment methods. Scatter plot shows the correlation between measured and predicted for content Zn, Mg, Fe, Cu whereas linear line fitted between them which describes how data is positively correlated.



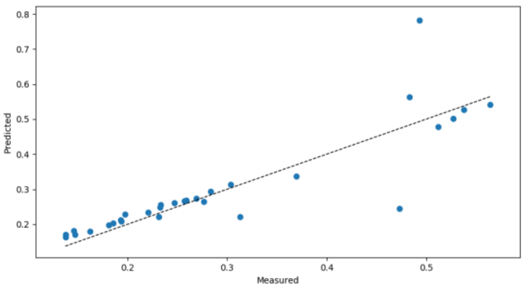

(a)



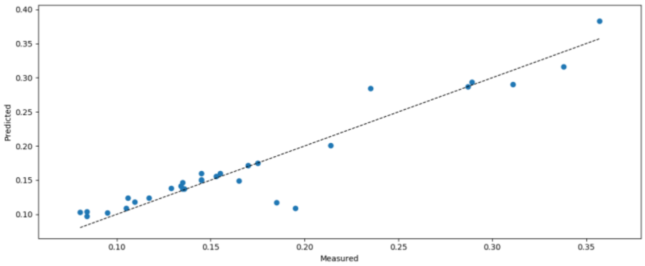

(b)




(c)




(d)




(e)

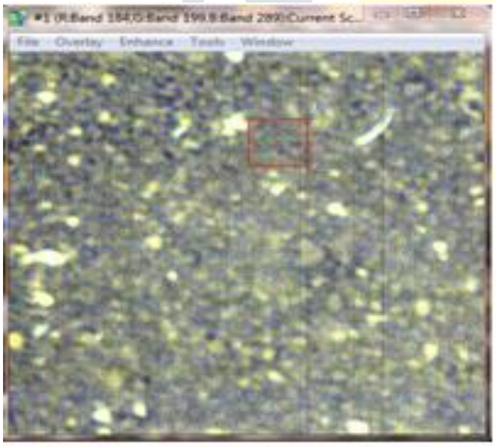
Figure.5 Scatter plot after preprocessing Fig.(a)Zn, Fig(b)Fe, Fig.(c)cu, Fig.(d)Mg, (e)moisture

Table no.3. Prediction result after pretreatment

| | Training | | Testing | |
|---|---|---|---|---|
| Contents | $R^2$ | RMSE | $R^2$ | RMSE |
| Zn | 0.903 | 0.036 | 0.829 | 0.053 |
| Fe | 0.829 | 0.0037 | 0.903 | 0.052 |
| Cu | 0.948 | 0.028 | 0.804 | 0.083 |
| Mg | 0.952 | 0.018 | 0.862 | 0.026 |
| Moisture | 0.954 | 0.0148 | 0.8892 | 0.0268 |
| Ph | 7.5 | | | |

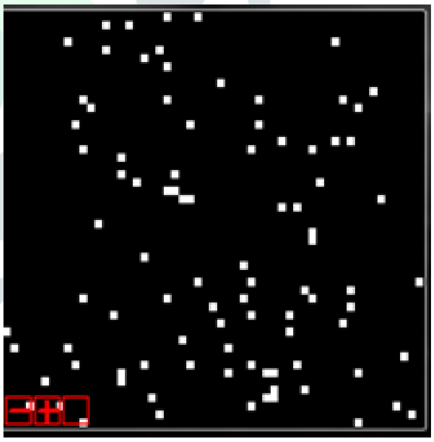
After pretreatment method (FD) the calibration prediction accuracy significantly increased results as shown in table no.3, with results for Zn $R^2$ = 0.903 and RMSE = 0.0306, For Fe $R^2$ = 0.829 and RMSE = 0.0037, other positive results also recorded for Cu and Mg with $R^2$ = 0.948, $R^2$ = 0.952 and RMSE = 0.028, 0.018 respectively. Moisture noticed bands 908nm and 1900nm with result recorded $R^2$ = 0.873, RMSE = 0.05 by using indices. Whereas scatter plot fig.5 shows significant positive correlation between predicted and measured values with linear fitted line which indicate good prediction result.

Selected band image which is raw original image shown in figure no.6. Indices method is used to differentiate the micronutrient from original raw image, as per the band math function applied by using indices it classifies the image where the micronutrients included within defined bands as above mentioned in eq. (5).



raw sample images

Figure no.6



normalised image for Fe content

Figure. no.7

Total number of points 1080000 are in image scale, values is between 0-1 where with minimun o values is with black pixcel and maximum 1 values is with white pixcel respectively. Where as pixel value with positive 1 represent that geothite part of iron present in image as shown in fig.7.

## V. CONCLUSION

Soil micronutrients can successfully detected through spectroscopy data. Applying spectral transformation FD and processed input to the PLSR regression algorithm for the calibration prediction model of micronutrients whose correlation coefficients result ($R^2$) for Zinc, Iron, Copper, Magnesium are 0.903, 0.829, 0.948, 0.952 with RMSE 0.036, 0.0037, 0.028, 0.018. So with the spectral and spatial features of hyperspectral data has great potential in monitoring the contents present in soil with the help of PLSR regression method. But with the hyperspectral imagery spectroradiometer has limitation up to (400-1000nm), to estimate these soil content features, it requires further wavelength range. As per the study of Field spect4 has ability to collect all granular materials reflectance properties not only extract the features and also very effective to estimate the required soil physiochemical contents.

## VI. ACKNOWLEDGMENT

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