Eco. Env. & Cons. 29 (1) : 2023; pp. (191-194)

ISSN 0971–765X

DOI No.: http://doi.org/10.53550/EEC.2023.v29i01.031

The Utility of Airborne Hyperspectral Measurement in Assessment of Soil Fertility

Raghu R.S.[1], P.R.K. Prasad[2] and K.V. Ramana[3]

[1]Department of Soil Science and Agricultural Chemistry, Agricultural College, Bapatla, Andhra Pradesh, India
[2]ARS, Amaravathi, Andhra Pradesh, India
[3]PPEG, NRSC, Hyderabad, Telangana, India

(Received 24 September, 2022; Accepted 12 November, 2022)

ABSTRACT

A study was undertaken to evaluate the correlation between hyperspectral data with soil fertility status in the study area of Chinnapalem village Guntur district, Andhra Pradesh. One hudredfifty-three (153) samples were collected at different locations with GPS coordinates by adopting grid method. The hyperspectral data revealed that soil reaction, available Mg, Zn, Fe, Cu and Mn showed positive and significant correlation between VIS-NIR region of electromagnetic spectrum. However, EC and available S were negative and significant throughout VIS and SWIR. From, Stepwise regression approach the poorest fit was observed in all the properties although the highest accuracy (R^2=0.467) was found for available zinc, while lowest predictability (R^2=0.028) was for sand.

***Key words**: Soil Fertility, Hyperspectal Remote Sensing, GPS, GIS, Correlation and MLR*

Introduction

Hyperspectral remote sensing (HRS) is one of the advanced technologies of remote sensing which began in early 1980's is one of the most significant breakthroughs in remote sensing. Hyperspectral sensors collect information as a series of narrow and contiguous wavelength bands at 10 to 20 nm intervals. It is a promising tool for its capability to measure the reflectance of earth surface features such as soil, water, vegetation, *etc*. at hundreds of continuous and narrow wavelength bands. Availability of such a large pool of spectral information offers an opportunity to estimate multiple soil attributes from the same reflectance with greater specificity (Sahoo *et al.*, 2015). Diffuse reflectance spectroscopy in the visible, near-infrared and short-wave infrared regions (350-2500 nm) forms the basis for hyperspectral remote sensing. Diffuse reflectance spectroscopy may be used for estimating several soil properties such as soil texture, organic carbon content, nutrient content such as nitrogen, phosphorus, potassium, electrical conductivity, CEC, Fe content, soil moisture content, carbonates and hydraulic properties of soil. Spectral mapping of specific soil properties will provide further assistance to soil pedologists in the development of soil surveys. Hence, Hyperspectral remote sensor data is used for the assesement of soil fertility status in chinnapalem village.

Material and Methods

Study area and soil sampling

The study area selected was Chinnapalem village in

[1]PhD Scholar, [2]University Head, [3]Group Director

Duggirala Mandal of Guntur district at Andhra Pradesh (Fig. 1). Considering the uniformity of soil sample distribution in the study area, one hundred fifty-three (153) surface soil samples were collected at a depth of 0-15 cm in a systematic pattern from different locations using grid map and GPS (GAGAN) having approximate grid interval of 500 m leaving water bodies, settlements and hills. Collected surface soil samples were air-dried, crushed and sieved (2 mm).

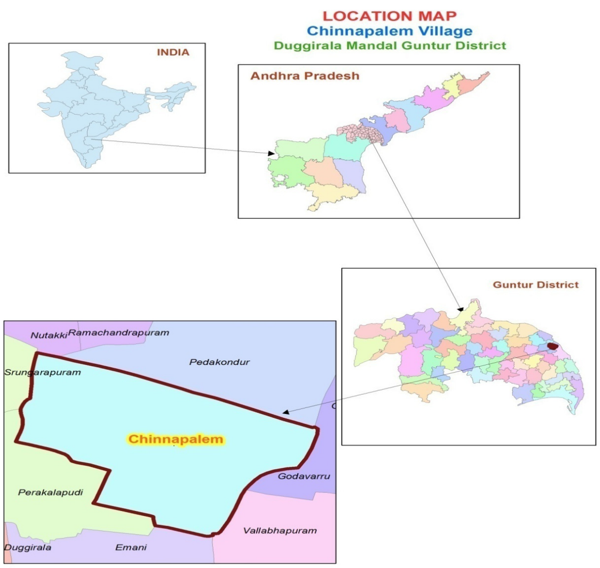

Fig. 1. Location map of Chinnapalem village of Guntur district in Andhra Pradesh

Hyperspectral data acquisition

The Airborne Visible and Infrared Imaging Spectrometer-Next Generation (AVIRIS–NG) hyperspectral sensor was flown over the site in the month of 28th May 2018. The AVIRIS–NG images, acquired at 2200 m above ground level, produced 5 m spatial resolution with 425 bands, covering the spectral range from 400 to 2500 nm with a 5 nm bandwidth.

Data analysis

Image processing and initial statistical analysis were conducted using ENVI 4.1 software (APSAC, Vijayawada). A circular area, made large enough to include 150 pixels (about a 7.6 m radius), was selected at each sample site, and the average reflectance for each of the 425 bands was exported as an ASCII file for further processing. These files were later opened in a spread sheet programme and further analyses were carried out.

Correlation analysis was performed for each soil property with each band. Best correlated bands from each reflectance related data sets were selected separately for each soil property, considering the absolute values of correlation coefficients.

Stepwise multiple linear regressions is concentrated to find the combination which is called linear discriminate function against the variables and the discriminate score. The linear expression is as follows:

$$D = B_0 + B_1X_1 + B_2X_2 + \ldots\ldots.. B_nX_n$$

Where, D is a discriminate score

B_0 is estimated constant

B_n are estimated coefficients

X_n are the variables

Model predictability (R^2) was used for evaluating the spectral data sets for prediction of soil properties. Spectral data set with highest R^2 was selected for model development for each soil property using SPSS-16.0 version software.

Results and Discussion

The spectral reflectance of soils was decreased with increasing clay content whereas it increased with increasing sand. Spectral correlation analysis for clay and silt was positive and high at bands 423 (r = 0.110) and 196 (r = 0.125), respectively. The high positive correlation may be due to finer nature of clay and silt as reported by Shepherd and Walsh (2002); Cozzolino and Morón (2003) and Viscarrarossel *et al.* (2006).The spectral correlation analysis for sand was negative and high at band 289 (r = -0.102). The high negative correlation may be due to low sand with low reflectance. Similar result at VIS-NIR (400-2500nm) was reported Shepherd and Walsh (2002), Cozzolino and Morón (2003) and Detar *et al*. (2008).

Soil reaction (pH) had an important implication in soil fertility assessment and was diagnostic in terms of classifying soils. Spectral correlation analysis for soil pH revealed that maximum bands were positive and significant. The highest correlation (r = 0.301**) was obtained at band 71. Similar results at VIS-NIR (350-2500 nm) were reported by Shepherd and Walsh (2002). Spectral correlation analysis for soil EC also revealed that the correlation was negative and significant (r = -0.089**) in band 207. Similar findings VIS-NIR (350-2500 nm) was reported by Islam *et al.* (2003) and Kaduputiya *et al*. (2009).

Soil organic carbon in the study area had unique spectral reflectance characteristics in the visible and near infrared regions. The spectral correlation analysis of soil organic carbon was negative without showing any significance. The highest value was found in band 1 (r = -0.136). These results were in good agreement with the findings of Islam *et al.* (2003) and David (2009). Correlation for available nitrogen and spectral reflectance was negative without any significance. The highest value was observed in band 422 (r = -0.136). Similar findings were observed by Gmur *et al*. (2012) in parts of Washington and Oregaon regions in U.S.A. The available P_2O_5 and K_2O in surface soil samples of study area was correlated positively in visible region to short wave infrared had correlation coefficient value of r = 0.154 (band 290) and r = 0.111 (band 72), respectively.

Spectral correlation analysis for available Ca was positive and high at band 423 (r = 0.116). Similar result at VIS-NIR (350-2500 nm) was reported by Islam *et al.* (2003) and Viscarrarossel *et al.* (2006). Spectral correlation analysis for available Mg was significantly positive and high at band 10 (r = 0.169*). Similar result at VIS-NIR (350-2500 nm) was reported by Shepherd and Walsh (2002). The available sulphur assement by hyperspectral remote sensing revealed that it was negative and significantly correlated throughout visible and SWIR regions. The highest values were observed in bands 6 and 7 with correlation coefficient value of r = -0.192*. Similar trend was observed by Kadupitiyo *et al*. (2009) in Jalandhar region of Punjab using hyperspectral remote sensing.

Spectral correlation analysis for DTPA extractable Zn, Cu, Fe and Mn in surface soils of study area were positive and significantly correlated throughout visible and SWIR. The highest values were found in band 209 (r = 0.239**), band 421 (r = 0.218*), band 196 (r = 0.170*) and band 422 (r = 0.240**) for Zn, Cu, Fe and Mn, respectively. Similar result at VIS-NIR (400-2498 nm) was reported by David (2009) and Rajeshwar and Mani, (2017).

Stepwise regression approach was used and results revealed that models developed using spectral data were not able to estimate the soil properties with reasonably higher accuracy. The poorest fit was observed in all the properties although the highest accuracy (R^2=0.467) was found for available zinc which was followed by available Mn (R^2=0.216), available Cu (R^2=0.175), available sulphur (R^2=0.153), available Fe (R^2=0.131), pH

Table 1. Prediction equations for relating soil properties from reflectance spectra

Model No.	Soil property	Regression equation	R^2
1	Clay %	=60.063-14.121 (Band291)	.029
2	Silt (%)	=7.932-0.661 (Band300)+1.095 (Band202)+32.928 (Band 289)	.108
3	Sand (%)	= 29.106+14.130 (Band291)	.028
4	pH	=7.151978+2.189281(Band71)+0.064148(Band294)	.124
5	EC (dS m^{-1})	=0.611+4.106 (Band289)-3.188(Band290)	.070
6	OC (%)	=0.337+0.169 (Band291)	.030
7	Available N (kg ha^{-1})	=272.808+74.453 (Band291)	.049
8	Available P_2O_5 (kg ha^{-1})	=48.193 -2.657(Band299) +134.607 (Band290)	.066
9	Available Calcium (mg kg^{-1})	=7902.764 -215.875 (Band295)+7525.314 (Band72)	.060
10	Available Magnesium (mg kg^{-1})	=1215.655 - 319.795 (Band200)	.033
11	Available Sulphur (ppm)	=12.058-340.634 (Band7)+17.204(Band304)-118.791 (Band422)+365.443 (Band16)	.153
12	Available Zinc (ppm)	=1.390+9.296 (Band209)-2.875 (Band304)-206.484 (Band368)+75.504 (Band367)+20.663 (Band326)-8.701 (Band424)+138.525 (Band371)-100.756 (Band400)+53.218 (Band406)-39.071 (Band328)+32.939 (Band327)+20.834 (Band420)	.467
13	Available Iron (ppm)	=5.651-0.226(Band297)+44.287 (Band314)-39.188 (Band326)	.131
14	Available Copper (ppm)	= 16.667-194.817 (Band4)+40.106 (Band266)	.175
15	Available Manganese (ppm)	=23.966-16.542 (Band291)-621.998 (Band7)+152.962 (Band422)+354.333 (Band3)	.216

(R^2=0.124), silt (R^2=0.108), EC (R^2=0.070), available P_2O_5 (R^2=0.066), available Ca (R^2=0.060), available nitrogen (R^2=0.049), available magnesium (R^2=0.0.33), organic carbon (R^2=0.030), clay (R^2=0.029), while lowest predictability (R^2=0.028) was for sand. Similar results were observed by Detar *et al*. (2008) and Sashikala *et al*. (2019).

Conclusion

Soil reflectance is affected by soil physical, physico-chemical and chemical properties. Correlation analysis of the spectral data with soil properties indicated that which parameter affected what part of the electromagnetic spectrum. An aircraft based sensor could provide the fine resolution required for site specific farming. The within field spatial distribution of some soil properties was found by using multiple linear regressions to select the best combinations of wave bands. The spectral information of the visible, near-infrared and short-wave infrared (VIS-NIR-SWIR; 400-2500 nm) spectral regions provided a promising capability to identify soil, vegetation, rock and mineral materials.

Acknowledgements

I owe a lot to Acharya N. G. Ranga Agricultural University for giving me this opportunity to do a doctoral study and providing me financial assistance in the form of a stipend, which was very useful during the course of my work. I am very much grateful to Andhra Pradesh Space Application Centre (APSAC), Vijaywada, Andhra Pradesh State Development Planning Society (APSDPS), Vijayawada, National Remote Sensing Centre (NRSC), Hyderabad, for the facilities and help provided during the present study. Special thanks go to the reviewers who contributed many good ideas to the manuscript.

References

Cozzolino, D. and Morón, A. 2003. The potential of near-infrared reflectance spectroscopy to analyse soil chemical and physical characteristics. *J. Agric. Sci.* 140: 65-71.

Detar, W. R., Joseph Chesson, H., John Penner, V. and John Ojala, C. 2008. Detection of Soil Properties with Airborne Hyperspectral Measurements of Bare Fields. *American Soci. Agric. and Bio. Eng.* 51(2): 463-470.

David, S. 2009. *Descriminating and mapping soil variability with hyper spectral reflectance data*. Thesis presented for the degree of Doctorate of Philosophy Faculty of Sciences, School of Earth and Environmental Sciences. The University of Adelaide. pp. 1-121.

Gmur, S., Vogt, D., Zabowski, D. and Moskal, M.L. 2012. Hyperspectral Analysis of Soil Nitrogen, Carbon, Carbonate, and Organic Matter Using Regression Trees. *Sen.* 12: 10639-10658.

Islam, K., Singh, B. and McBratney, A. 2003. Simultaneous estimation of several soil properties by ultra-violet, visible and near-infrared reflectance spectroscopy. *Aus. J. Soil Res.* 41: 1101-1114.

Kadupitiya, H.K., Sahoo, R.N., Ray, S.S., Gupta, V.K., Ahmed, N., Sahoo, P.M., Chakraborty, D. and Chopra. U.K. 2009. *Quantitative Assessment of Soil Propertiesusing Proximal Hyperspectral Remote Sensing*. Ph. D. Thesis for the degree of Doctorate of Philosophy, ICAR, New Delhi..

Rajeshwar, M and Mani, S. 2017. Detection of some soil properties using hyperspectral remote sensing of semi arid region of Tamil Nadu. A*sian. J. of Soil Sci*. 12 (1): 191-201.

Sahoo, R.N., Ray, S.S. and Manjunath, K.R. 2015. Hyperspectral remote sensing of Agriculture. *Curre. Sci.* 108 (5): 848-859.

Sashikala, G., Naidu, M.V.S., Ramana, K.V., Nagamadhuri, K.V., Pratap, K.R.A., Sudhakar, P and Giridhar, K.T. 2019. Characterization and Classification of Soils in Semi Arid region of Tatrakallu Village of Anantapuramu district in Andhra Pradesh. *J. Ind. Soc. Soil Sci.* 67(4) : 3898-401.

Shepherd, K.D. and Walsh, M.G. 2002. Development of reflectance spectral libraries for characterization of soil properties. *Soil. Sci. Soc. Americ. J.* 66: 988-998.

Viscarra Rossel, R.A., Walvoort, T.D., McBratney, A.B., Janik LJ. and Skjemstad J.O. 2006. Visible, near infrared, mid infrared or combined diffuse reflectance spectroscopy for simultaneous assessment of various soil properties. *Geoderma.* 131 : 59-75.