USE OF HIGH RESOLUTION REMOTE SENSING DATA FOR GENERATING SITE-SPECIFIC SOIL MANGEMENT PLAN

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ABSTRACT:

This present study explores the use high-resolution multi-spectral remote sensing data for generating within-field soil variability map as an inputs required for site-specific management of agriculture. The study was conducted for an experimental plot in Central Potato Research Station of Jalandhar, India. Thirty-five soil samples were collected from the field at regular intervals. The samples were analyzed for soil organic carbon, available nitrogen, available phosphorus, available potassium and soil texture. Various soil-related indices were calculated from IKONOS multispectral data, which included Brightness Index (BNI), Hue Index (HI), Saturation Index (SI), Coloration Index (CI), Redness Index (RI) and three principal components (PC1, PC2 and PC3). Variability of soil and spectral parameters were analyzed by estimating coefficient of variation (CV). The correlation analysis was carried out to study the relationship between soil and spectral parameters. Multiple regression models were generated, using stepwise regression technique, to estimate soil properties from RS data. The results showed that, CV of soil parameters was highest for available P (29.9%), followed by silt percentage (20.8%). Among the spectral parameters the CV was highest for PC3 (161.9%), followed PC2 (101.4%) and PC1 (84.0%). The soil organic carbon, available N and silt content were significantly correlated with spectral indices. The multiple regression equation between OC and spectral indices was significant with R = 0.733 and F = 6.277. Available N, silt and sand also formed significant multiple regression equations with spectral parameters. These empirical equations were used to generate soil fertility variability plans.

1. INTRODUCTION

It is well known that large variation occurs in soil parameters, even within a field. One of the objectives of precision farming is to fine tune the management practices to match this variability, and thus improve the productivity or reduce the cost of production and also diminish the chance of environmental degradation caused by excess use of inputs (Pierce and Nowak, 1999). Hence, soil fertility variability map is one of the major inputs required for site-specific management of agriculture. Conventionally this is generated by interpolation of soil samples taken at regular intervals. However, this approach has the limitation of large area applicability as it is time consuming and costly. As against the traditional method of soil sampling and laboratory analysis of soils, image based remote sensing is an efficient, fast and economically sustainable way to detect spatial difference in crop and soil conditions within field. It offers the potential for identifying fine-scale spatial patterns in soil properties across a field and optimizing soil sampling strategies to quantify these patterns (Mulla et al., 2000). Several soil properties, namely, surface condition, particle size, organic matter, soil colour, moisture content, iron and iron oxide content and mineralogy have been found to affect their spectral behaviour (Dwivedi, 2001). Organic matter is the dominant factor in determining soil spectral behaviour when it is present in quantities more than 2 per cent (Baumgardner et al., 1970). According to the study by Coleman and Montgomery (1987), an increase in soil moisture and organic matter content resulted in a decrease in the reflectance values. They showed that near infra red bands (0.76-0.90 μm) were best related to organic matter. Similarly, soil texture also significantly influences the reflectance pattern. Fine textures generally show greater reflectance than coarse textures (Horvath et al., 1984). In order to explore the relationships between remote sensing based spectral reflectance and soil parameters a number of indices, like, brightness index, hue index, reflectance index, principal component analysis (PCA), etc are used. The study carried out by Leone et al. (1995) shows that organic matter is significantly related to brightness index. Ray et al. (2001, 2002) have shown the usefulness of using brightness index in quantifying within-field variability. Suk. et al. (2002) in their study has shown how the principal component 2 and 4 are strongly correlated to soil chemical properties like, organic matter, magnesium (Mg), and potassium (K) contents. In the recent past, very high resolution remote sensing (RS) data, such as IKONOS Multispectral is emerging as a tool for such purpose. This present study explores the use high-resolution multi-spectral remote sensing data for generating within-field soil variability map.

2. STUDY AREA

The study was carried in the farm of Central Potato Research Station (31.16^0N latitude and 75.32^0E longitude) in Jalandhar, Punjab state of India. The farm follows potato-wheat crop rotation. The soil type of the farm was ranging from very deep sandy loam, very deep loam to very deep clay loam. The study was carried out during April in one of the fields having an area of 4.43 ha, where the land was fallow after the harvest of potato crop. IKONOS multi-spectral data of 30th April 2001 shows the layout of the farm and the study field (Figure 1).

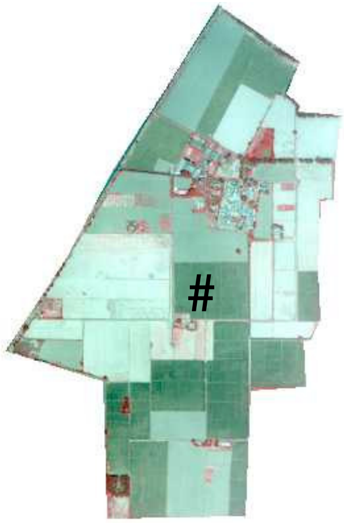

Figure 1. IKONOS image of 30th April, 2001 showing the CPRS farm (# is the field where soil variability was studied)

3. METHODOLOGY

3.1 Remote Sensing Data

IKONOS multi-spectral data of 30th April 2001 was acquired and during the period, when the field was fallow. The IKONOS satellite (Space Imaging, Thronton, CO, USA) was launched into low earth sun-synchronous orbit in September 1999. IKONOS provides images in panchromatic mode (0.45-0.90 µm), with 1m spatial resolution and multispectral mode with 4 m spatial resolution (table 1). The data is available in 8-bit or with full dynamic range 11-bit radiometric resolution. For the present study 11 bit data was used. The data is delivered in georeferenced format with UTM projection and WGS84 datum.

Table 1. IKONOS spectral band characteristics

Band	Band Centre (nm)	Bandwidth (nm)	Calibration Coefficient@ [mW/(cm^2*sr*DN)]
Blue (MS-1)	480.3	71.3	728
Green (MS-2)	550.7	88.6	727
Red (MS-3)	664.8	65.8	949
VNIR (MS-4)	805.0	95.4	843

@ For 11 bit products (post 22/02/2001)
(Source: http://www.spaceimaging.com/products/ikonos/spectral.html)

3.2 Soil Parameters

Thirty-five soil samples (surface soil) were collected from the field at regular intervals. The samples were analyzed for soil organic matter (%), available nitrogen (ppm), available phosphorus (ppm), available potassium (ppm) and soil texture (sand, silt and clay percentage). The methodology for determining soil chemical (fertility) parameters is given in Table 2. Soil texture was determined using International Pipette method. As soil texture analysis a very time consuming process only twelve samples (every third sample) were analyzed.

Table 2. Methodology for determining soil chemical parameters

Parameter	Method	Reference
Organic Matter	Chromic acid titration	Walkley and Black (1934)
Available N	Alkaline Permanganate Extractable Method	Subbiah and Asija (1956)
Available P	Sodium Bicarbonate Extr. Method	Olsen et al. (1954)
Available K (Exch.+ Soluble)	Ammonium acetate Extr. Method	Muhr et al. (1965)

3.3 Computation of Spectral Indices

Various soil-related spectral indices were calculated from IKONOS MS data, after converting the digital numbers into radiance values. Those indices included soil related indices such as, Brightness Index (BNI), Hue Index (HI), Saturation Index (SI), Coloration Index (CI) and Redness Index (RI). The method for estimating these indices is presented table 3. Apart from these three principal components (PC1, PC2 and PC3) were also generated using principal component analysis (PCA). PCA has been used for dimensionality reduction of multispectral images in pattern recognition applications and for creating an optimal set of spectral information from a large number of bands.

Table 3. Radiometric indices calculated using hyperspectral data for soil property study (adopted from Mathieu et al, 1998)

Index	Formula	Index Property
Brightness Index, BI	$(R^2+G^2+B^2)/3.0)^{0.5}$	Average reflectance magnitude
Saturation Index, SI	(R-B)/(R+B)	Spectra Slope
Hue Index, HI	(2*R-G-B)/(G-B)	Primary colours
Coloration Index, CI	(R-G)/(R+G)	Soil Colour
Redness Index, RI	$R^2/(B*G^3)$	Hematite Content

3.4 Variability study of parameters

Variability of soil and spectral parameters was analyzed by estimating coefficient of variation (CV) of the soil and the spectral parameters. The correlation analysis was carried out to study the relationship between soil and spectral parameters. Multiple regression models were generated, using stepwise regression technique, to estimate soil properties from RS data. The empirical models were generated only for those parameters, where correlation was significant. These empirical equations were used to generate soil fertility variability maps from RS data.

4. RESULTS AND DISCUSSION

The IKONOS multispectral data was used to compute radiometric indices and the three principal components. The principal component analysis for the study field showed that the first principal component accounts for 91.7 percent of total variance in the dataset (Table 4). Combined, first and second and first, second and third contained 96.2 and 98.5 percent of total variance, respectively. Here the first three principal components were used in this study.

Table 4. The characteristics of the principal components from 4 band IKONOS MS data

Principal Compo-nent	Eigen-value	Deviation	Variance (%)	Cum. Variance (%)
1	646.2826	25.4221	91.69	91.69
2	31.6867	5.6291	4.50	96.19
3	16.5773	4.0715	2.35	98.54
4	10.3307	3.2141	1.47	100.00

4.1 The Variability Analysis

The mean, standard deviation and coefficient of variation of the soil and spectral parameters for 35 locations (12 locations for soil texture) are presented in table 5. Overall the soil has sandy loam texture with low organic matter, low available N, high available P and low available K. The variability analysis, as reflected by the coefficient of variation, showed that, among soil parameters the variability was highest for available P (CV=29.9%), followed by silt percentage (CV= 20.8%). Among the spectral parameters the CV was highest for PC3 (161.9%), followed PC2 (101.4%) and PC1 (84.0%).

Table 5. Variability of field and spectral parameters for the soil

Parameter	Mean	Std. Dev.	C.V. (%)
O.M.(%)	0.25	0.057	22.98
Available N (ppm)	103.23	14.22	13.77
Available P (ppm)	28.54	8.61	30.16
Available K (ppm)	100.34	20.70	20.62
Sand (%)	82.58	2.208	2.67
Silt (%)	8.05	1.678	20.84
Clay (%)	9.37	1.310	13.98
BI	0.61	0.016	2.65
SI	-0. 12	0.011	-8.97
HI	-3.92	0.498	-12.73
CI	-0.19	0.006	-3.34
RI	1.07	0.056	5.21
PC1	-0.18	0.155	-83.96
PC2	0.007	0.007	101.38
PC3	-0.003	0.005	-161.95

4.2 Analysis of Interrelationship of Variability

Among the soil fertility and textural parameters soil organic matter (OM), available N and silt content were significantly correlated with spectral indices (Table 6). The number of data points was 35 for OM, available N, Available P and available K and 12 for sand, silt and clay content. For soil organic matter highly significant correlations were found with the radiance of blue and green bands, brightness index and redness index. The red and VNIR band and the PC1 also produced significant correlations. Most of these correlations, except for RI and PC1 were negative. All the spectral bands and indices such as BNI, SI, HI and CI had significant negative correlations with available nitrogen. Available P and K did not have any significant correlation. Among the soil textural parameters, silt content had significant correlation with maximum number of spectral parameters. The sand and clay content had significant correlation with RI and CI, respectively.

Table 6. Correlation study of spectral parameters derived from IKONOS data and soil parameters

Spectral Para-meters	O.M. (%)	Avl. N (ppm)	Avl. P (ppm)	Avl. K (ppm)	Sand (%)	Silt (%)	Clay (%)
Blue	-0.584***	-0.295*	-0.160	-0.035	0.396	-0.600*	0.100
Green	-0.477**	-0.325*	-0.090	0.022	0.390	-0.505*	-0.011
Red	-0.365*	-0.367*	-0.096	-0.014	0.300	-0.512*	0.149
VNIR	-0.422*	-0.301*	-0.072	0.025	0.350	-0.530*	0.089
BNI	-0.474**	-0.344*	-0.097	0.010	0.420	-0.569*	0.021
SI	-0.136	-0.324*	-0.048	-0.030	0.024	-0.262	0.294
HI	-0.266	-0.331*	-0.007	-0.019	0.034	-0.192	0.188
CI	0.158	-0.209	-0.029	-0.080	-0.125	-0.222	0.496*
RI	0.546**	0.194	0.063	-0.044	-0.541*	0.501*	0.269
PC1	0.328*	0.047	0.103	-0.139	0.245	-0.306	-0.021
PC2	-0.194	-0.173	-0.002	0.043	0.133	-0.384	0.268
PC3	-0.251	0.125	-0.004	0.073	0.390	-0.169	-0.441

*$0.01<p<0.1$, **$0.001<p<0.01$, ***$p<0.001$

The multiple regression equations were generated between soil and spectral parameters using stepwise regression technique. Empirical equations were generated only for those parameters for which the correlations were significant (Table 7). The empirical relation between OM and spectral indices was highly significant with coefficient of determination R = 0.733 and F = 6.277. The sand, silt and clay content also formed significant multiple regression equations with spectral parameters. In each of these equations only one spectral parameter came into the equation. The multiple R for these equations ranged from 0.495 to 0.599 and F value ranged from 3.3 to 5.6. However, Available N, though individually had significant correlation with spectral parameters, did not form a significant multiple regression equation.

Table 7. Empirical equations between soil and spectral parameters derived using stepwise regression technique.

Soil Parameter	Regression Equation	Multiple R	F value
Organic Matter (%)	0.49+2.9*BNI-3.4*Blue – 0.5*HI + 0.06*PC1 + 2.9*SI	0.733	6.3***
Available N (ppm)	-2844.8-866.5*Blue + 9960.5*VNIR - 10767.2*PC2 - 6811.1*Red + 1070.5*RI	0.532	2.14
Sand (%)	103.9 - 19.96*RI	0.540	4.1*
Silt (%)	40.3 - 52.8*Blue	0.599	5.6*
Clay (%)	29.5 + 105.8*CI	0.495	3.3*

*0.01<p<0.1, **0.001<p<0.01, ***p<0.001

4.3 Variability map generation

The soil fertility parameter variability maps were generated for OM and available N from the RS data using the above-mentioned empirical equations. After generating the maps they were applied with a 3x3 average filter to remove the noisiness in the maps and then classified into four classes. The outputs are presented in figure 2. The classes for OM had average values of 0.23, 0.24, 0.25 and 0.26 percent, which are represented from dark to light tones in the figure. Similarly the three classes for available N had average values of 100.0, 105.0 and 120.0 ppm, again represented from dark to light tones in the figure. It may be mentioned that, the concerned field (4.43 ha), as per the conventional soil classification, had two major soil types such as sandy loam and clay loam. Thus the management practice based on conventional soil classification could have resulted into only two types, where as the remote sensing data, can identify more classes. These variability maps can be used for site-specific soil fertility management.

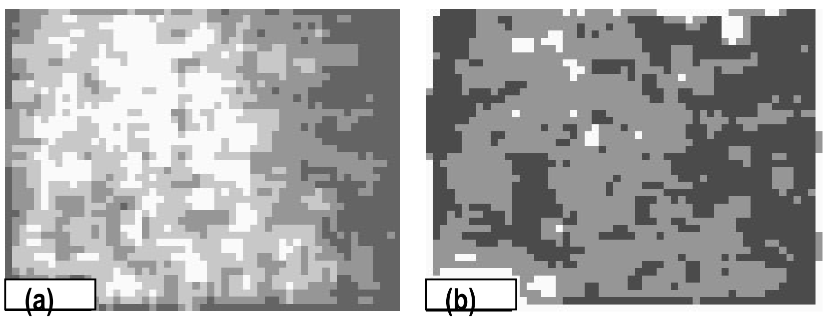

Figure 2. Soil fertility parameter variability maps generated from remote sensing data a) Organic matter per cent (0.23, dark – 0.26,light) b) Available nitrogen in ppm (100.0,dark – 120.0, light)

5. CONCLUSIONS

This study showed the usefulness of using high resolution multi-spectral remote sensing data for estimation of soil nutrient related parameters, and generate within field nutrient variability maps. For some of the parameters the poor correlations can be attributed to the time gap between soil observations and satellite pass. Thus, near synchronous data acquisition without time lag is a critical requirement for such studies. For further study, the data from LISS IV sensor (5.8 m resolution) on board Indian Resourcesat satellite is proposed to strengthen such findings.

REFERENCES

Baumgardner, M. F., Kristof, S.J., Johannsen, C.J., and Zachary, A.L., 1970. Effect of Organic Matter on multispectral properties of soils. *Proceedings of Indian Academy of Science,* 79, 413-422.

Coleman, T.L., and Montgomery, O.L., 1987. Soil moisture, organic matter and iron content effect on spectral characteristics of selected Vertisols and Alfisols in Alabama. *Photogrammetric Engineering and Remote Sensing,* 12, 1659- 1663.

Dwivedi, R.S.,2001 *Soil resources mapping: A remote sensing perspective. Remote sensing Review*, 20, 89-122

Horvath, E.H., Post, D.F., and Kelsey, J.B., 1984, The relationships of Landsat digital data to the properties of Arizona Rangeland. *Soil Science Society American Journal,* 48, 1331-1334.

Leone, A.P., Wright, G.G. and Corves, C., 1995. The application of satellite remote sensing for soil studies in upland areas of southern Italy. *Int. J. Remote Sensing*, 16, pp.1087-1105.

Muhr, G.R., Dutta, N.P., Sankarsubramaney, H., Leley, V.K. and Donahue,R.L., 1965. *Soil Testing in India*. 2nd Edn., U.S.A.I.D., New Delhi. pp 49.

Mulla, D.J., A.C. Sekely, and M. Beatty. (2000). Evaluation of remote sensing and targeted soil sampling for variable rate application of lime. CD-ROM. *In: P.C. Robert et al., (ed) Proc. 5th Intl. Conf. on Precision Agriculture, Minn., MN, Jul 16-19, 2000. ASA, CSSA, and SSSA, Madison, WI*

Olsen, S.R., Cole, V.C., Watanabe, F.S. and Dean, L.A., 1954, *Estimation of available phosphorus in soils by extraction with sodium bicarbonate*. U.S. Deptt. Agric. Circular No. 939.

Ray, S. S, Singh, Ashvir, Panigrahy, S., Singh, J. P. and Parihar, J.S. (2001) Precision Farming using high resolution remote sensing data – An exploratory Study for Indian context, ISRS Symposium, 2001, 11-13, December held at SAC, Ahmedabad.

Ray, S.S., Singh, J.P., Dutta, S. and Panigrahy, Sushma (2002) Analysis of within field variability of crop and soil using field data and spectral information as a pre-cursor to precision crop management. Int. Arch. PHotogramm. Rem. Sens. & Spatial Inform. Sytem, Vol. 34, Part-7, pp.302-307.

Subbiah, B.V. and Asija, C.L., 1956. A rapid procedure for the estimation of available nitrogen in soils. *Current Science,* 25, pp. 259-60.

Suk, Y.H., Sudduth, K.A., Kitchen, N.R., Drummond, S.T., Palm, H.L., and Wiebold, W.J., 2002. Estimating within field variations in soil properties from airborne hyperspectral images. *In Pecora 15/ Land Satellite Information IV/ ISPRS Commission I/ FIEOS 2002 Conference Proceedings*

Walkley, A. and Black, I.A., 1934. An examination of the Degtjareff method for determining soil organic matter and a proposed modification of the chromic acid titration method. *Soil Science*, 37, pp.29-38.

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