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Hyperspectral remote sensing for prediction of soil properties

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Abstract

This study was conducted to evaluate Hyperion satellite data along with field and laboratory spectral observations for predicting soil properties. The spectral observations of *in-situ* soils in the study area were taken at 85 random locations and soil samples of each location were scanned under laboratory conditions for recording reflectance spectra. Out of 242 bands of Hyperion satellite data, error free 158 bands were used for the study. Laboratory and field measured reflectance data were resampled to obtain Hyperion comparable 158 bands. Three data sets were used for developing prediction models for eight soil properties; Soil Organic Carbon content (SOC), $CaCO_3$, Mineralizable Nitrogen (N), available Phosphorous (P), available Potassium (K), sand %, silt % and clay %. Prediction models were developed using stepwise regression approaches. The study showed that the corrected Hyperion spectral pattern was comparable with ground-based spectra. Reflectance and derived spectra were used for models and derivatives were found as better predictors of soil properties than that of reflectance or absorbance, irrespective of the platform. Although the predictability of Hyperion reflectance is lower than that of field and laboratory reflectance, some soil properties such as Silt, SOC and $CaCO_3$ could still be predicted with reasonably good accuracy (R^2 > 0.5) with Hyperion data.

Key words: Field Spectra, Hyperion, Lab-spectra, Soil property prediction

Introduction

Environmental monitoring, crop modelling and precision agriculture research and applications need frequent and inexpensive soil data. Also, regional coverage and spatial variability are more valuable than point measurements for such techniques. Hence, rapid, cost-effective methodologies, which can generate spatial variability of soil properties are essential. Visible (VIS) and near-infrared (NIR) reflectance spectroscopy is a physically non-destructive, reproducible method that provides rapid prediction of soil physical, chemical and biological properties according to their reflectance in the wavelength range from 400 to 2500 nm (Ben-Dor and Banin, 1995; Reeves *et al*., 2000; Dunn *et al*., 2002; Shepherd and Walsh, 2002; Islam *et al*., 2003). Reflectance signals are produced due to vibrational frequencies combined with stretching and bending of chemical bonds in the NIR (700-2500 nm) and due to electronic transitions in the VIS (400-700 nm) portions of the electromagnetic spectrum (Ben-Dor *et al*., 1999). Using multivariate statistical approaches, laboratory and field measured reflectance data with high spectral resolution can be used to predict a wide range of soil properties (Viscarra *et al*., 2006; Kadupitiya *et al*., 2010). Compared to studies of using proximal (laboratory and field measured) reflectance spectra, fewer attempts have been found predicting soil properties using hyperspectral satellite imagery. Both proximal and remote sensing technologies have much in common, as they share the common goal of acquiring data on the spectral reflectance of earth surface materials from a remote location. Proximal spectroscopy is technically less challenging, as sensing instrument can remain fixed over the subject of interest for much longer and the path length between the instrument and the object being measured is reduced and field spectroradiometers generally measure a much smaller area (Milton *et al*., 2007). However, the transfer of relationships established at the laboratory level up to higher scales poses a number of problems associated with possible factors of confusion such as changes in soil roughness, moisture, illumination and view conditions and the presence and nature of pebbles. In addition, sensor characteristics such as spectral and spatial resolution, radiometric calibration may also change relationships between measured reflectance and actual soil characteristics in addition to possible atmospheric effects. Hyperspectral image records spatial variability of reflectance data belonging to each ground pixel in hundreds of narrow, contiguous spectral bands. Due to atmospheric influences and mixed pixel effects on the signals, the application of hyperspectral image data is still challenging to the research community (Chabrillat *et al*., 2002). Therefore, this study aims to evaluate hyperspectral remote sensing data for predicting important soil parameters such as available Mineralizable N, P, K, SOC, $CaCo_3$, sand, silt and clay content in soil and compare with predictions of proximal sensing approach with Spectroradiometer.

Materials and methods

Study area

As the study aimed at estimation of soil properties from hyperspectral satellite data the study area was defined based on the covering area of Hyperion satellite image. The study was carried in the North Western part of Punjab, India covering partly Jalandhar, Hoshiarpur and Ludhiana districts. The area is 7.36 x 106 km^2 strip along North-South direction having geographic extent from 30° 45′ to 31° 45′N latitude and 76° 25′ to 76° 45′E longitude, which is the swath of EO-1 Hyperion (Figure 1). The region is characterized by hot dry sub-humid to semi-arid transition with dry summers and cool winters. The soils of the region are generally deep to moderately deep, loamy and soil type is alluvial covering only two soil orders (Entisols and Inceptisols). The mean summer (May-July) temperature ranges from 33 to 34°C rising to maximum 40 °C in the month of June. The winter (Dec-Feb) average temperature ranges from 13 to 15 °C with a minimum of 4-8 °C during December and January. The annual average rain fall of the study area varies from 700 to 1000 mm and annual potential evapotranspiration range between 1300-1500 mm. Most of the area is under irrigated agriculture and is known for rice-wheat cropping system and the other major crops of this area are maize, sugarcane, cotton, and groundnut.

Sampling locations

A field survey was conducted synchronizing the date of the satellite (Hyperion) passing over the study areas. Test sampling locations were selected representing whole study area. All the test locations were consisted with continuous bare agricultural fields and disturbed soil samples (1 kg) were collected from surface 0-10 cm soil layer form randomly selected 85 test locations, followed by spectral measurements. Distribution of sampling locations are illustrated in Figure 1.

Hyperspectral data

The EO1-Hyperion satellite data (path: 148, row: 38) of 12th May 2008 at 05:20 GMT with scene centre Lat: 31.22° and Lon:75.53° were used for the study. In the Hyperion image, 35 bands in the visible region, 35 bands in the near-infrared region and 172 bands in short wave infrared region are normally available (Beck, 2003). Hyperion data processing in this study includes correction for stripping pixels, atmospheric correction and geo-rectification. Radiance data in original Hyperion images were converted into reflectance data using FLAASH (Fast Line-of-sight Atmospheric Analysis of Spectral Hypercubes) atmospheric correction software, following Beck (2003). All the hyperspectral image analyses were performed using ENVI (Ver 4.5) software.

Field spectral reflectance were recorded using Analytical Spectral Device (ASD) Field Spec™3 spectroradiometer which was specifically designed for use under field and laboratory condition to record measurement of reflectance in Visible Near-Infra Red (VNIR) and Short-Wave Infra-Red (SWIR) regions. Spectral measurements were recorded under standard illumination conditions using two calibrated tungsten quartz halogen lamps as an only light source in dark room condition for all 85 samples, after air drying and sieving the soil through 2 mm mesh sieve.

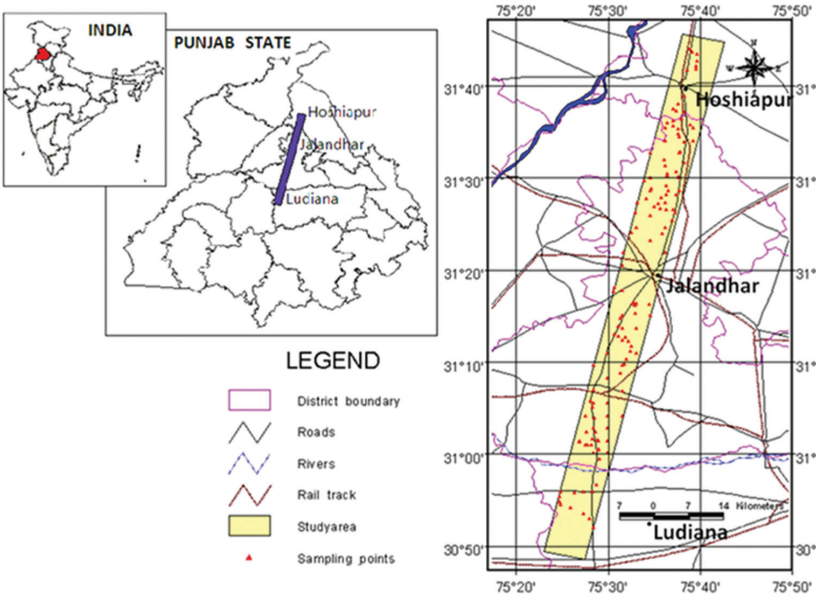

Figure 1. Location Map of the study area showing red dots as soil sampling points

Soil data

Chemical and physical properties were determined using standard methods. Walkley and Black (1934) method was used for the estimation of soil organic carbon (SOC). Mineralizable nitrogen (N) was estimated using Kjeldahl distillation method (Subbiah and Asija, 1956). Ascorbic acid method (Watanabe and Olsen, 1965) was used with a spectrophotometer for estimation of available Phosphorous (P). Ammonium acetate method (Hanway and Heidal, 1952) with flame photometer was adopted for estimation of available potassium (K). Calcium carbonate ($CaCO_3$) was estimated using rapid manometric method using Calcimeter (Williams, 1949). Sand (2.0-0.05 mm), silt (0.05-0.002 mm) and clay (<0.002 mm) content were determined using Bouyoucos Hydrometer method with ASTM 152H hydrometer (Bouyoucos, 1962).

Spectral data pre-processing

Processing of spectral data includes deriving absorbance from reflectance spectra, computation of derivative data sets for ASD spectral data and extracted Hyperion reflectance data. Absorbance has been calculated using relationship "absorbance = $\log_{10}$ (1/reflectance)" using ViewspecPro ver 3.0 software. First and second derivatives of reflectance and absorbance were calculated for all the spectral data sets. Absorption features in reflectance spectra were enhanced using derivative spectroscopy. The process of creating derivative spectra proceeded using a finite approximation to calculate the change in reflectance over a bandwidth $\Delta\lambda$, defined as $\Delta\lambda = \lambda j - \lambda i$, where $\lambda j > \lambda i$ (Tsai and Philpot, 1998). The equations for the first derivative (Eq 1) and nth derivative (Eq 2) are shown below;

$$\left.\frac{ds}{d\lambda}\right|_i = \frac{S(\lambda_i) - S(\lambda_j)}{\Delta\lambda} \qquad \text{(Eq. 1)}$$

$$\left.\frac{d^n s}{d\lambda^n}\right|_j = \frac{d}{d\lambda}\left(\frac{d^{(n-1)}s}{d\lambda^{(n-1)}}\right) \qquad \text{(Eq. 2)}$$

where,

$s(\lambda_i)$ is spectral reflectance/absorbance at λ_i^{th} wavelength/band.

A total of six sets of spectral data was generated as shown in Figure 2. The same process was repeated for spectral reflectance collected in field and laboratory condition and extracted from Hyperion reflectance image.

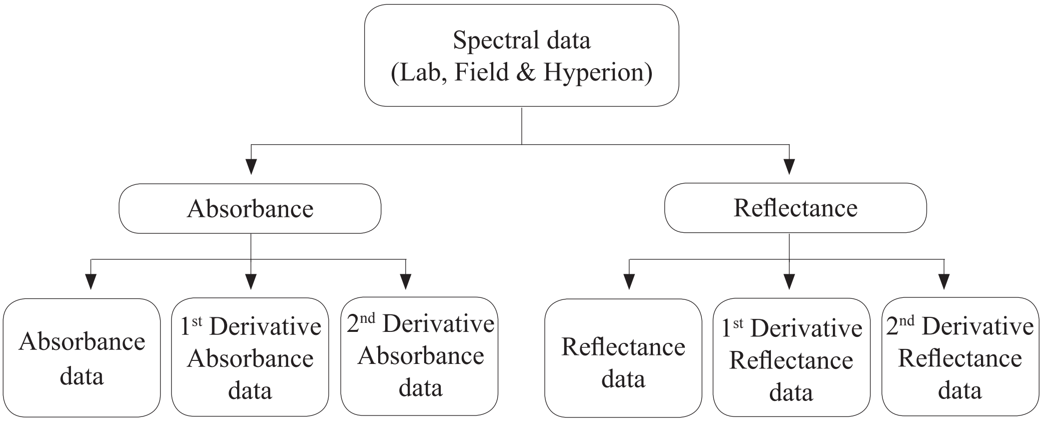

Figure 2. Data sets derived through mathematical manipulation of spectral data

As one of the objectives of this study is to compare the ground collected spectral data with that of Hyperion for estimation of soil properties, the spectral data collected at 1 nm were resampled to 10 nm (i.e. spectral resolution of Hyperion) using spectral response function of Hyperion through the following mathematical expression (Eq. 3);

$$r_i = \frac{\sum_{\lambda l_i}^{\lambda u_i} r(\lambda)\, \varphi_i(\lambda)}{\sum_{\lambda l_i}^{\lambda u_i} \varphi_i(\lambda)} \qquad \text{(Eq. 3)}$$

where, r_i is the reflectance of band i^{th} Hyperion sensor, λui is the upper boundary of band i, λli is the lower boundary of band i, $r\,(\lambda)$ is the reflectance for wavelength i, $\varphi(\lambda)$ is the spectral response function of band i. Three sets of spectral data set i.e. Laboratory (ASD-Lab), Field (ASD-field), and Hyperion having absorbance, reflectance, and their first and second derivatives were further analysed for correlating with selected soil properties. Bivariate correlations analysis was done between soil properties and 6 spectral data sets using SPSS software. Correlation analysis in SPSS software was performed for each soil property for 2/3rd data records. Best correlated 30 bands from each reflectance related data sets were selected separately for each soil property, considering the absolute values of correlation coefficients. The prediction model was developed for each soil property considering all the 30 bands as the predictive variable. Model predictability (R^2) was used for evaluating the spectral data sets for soil properties. Spectral data set with highest R^2 was selected for model development for each soil property. During model development adjusted R^2 was used for selecting the model and the optimum number of independent variables (bands) in each model for each soil property. Adjusted R^2 is a modification that adjusts for the number of explanatory terms in a model. Unlike R^2, the adjusted R^2 increases only if the new term improves the model more than would be expected by chance. Adjusted R^2 is particularly useful in the feature selection stage of model building. However, number of bands to be considered for prediction equation of each soil parameter was decided based on the adjusted R^2 values. Stepwise regression procedure in SPSS software was used for development of parameter prediction models. 2/3rd of 85 soil sample data was used for development of spectral prediction model for different soil properties. The remaining 1/3rd of the data records was used for validation.

Results and discussion

Pre-processing of Hyperion data

The Hyperion sensor data received was having 242 bands out of which 22 bands were overlapping. As per header information provided with image data, 84 bands were excluded during pre-processing due to non-calibration, stripping and overlapping. Finally, only 158 bands were selected after FLAASH correction. Water vapor amount is one of the major uncertain factors in the atmospheric components that affect radiation in the 0.4-2.5 µm spectral regions. FLAASH includes a method for retrieving the water vapour amount for each pixel. This technique produces a more accurate correction than using a constant water vapour amount for the entire scene. To use this water vapour retrieval method, the image must have bands that span at least one of the following ranges such as 1050-1210 nm (for the 1135 nm water absorbance), 870-1020 nm (for the 940 nm water absorbance) and 770-870 nm (for the 820 nm water absorbance). Scale adjusted three reflectance data sets were compared. The comparison of three reflectance spectra is given in Figure 3.

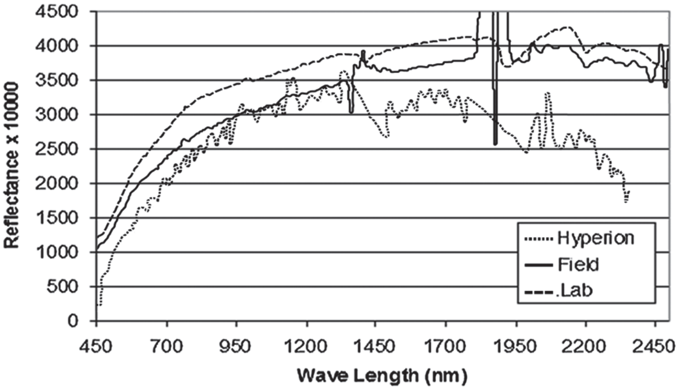

Figure 3. Comparison of reflectance spectral pattern

Soil properties

The descriptive statistics of 8 soil properties namely available mineralizable N, P, K, $CaCo_3$, SOC, percent sand, silt and clay of 85 soil samples collected from the study area are given in Table 1. Although, soil samples were collected from a defined area of 7.36 x 106 km^2, soil properties exhibit wider variation and allow developing better models that are valid for wider range of property values.

Table 1. Description of soil chemical and physicochemical properties of the study area

Parameter	Min	Max	Mean	Std. Dev
Mineralizable Nitrogen (mg/kg) (N)	69.0	207.0	122.3	28.7
Available Phosphorous (mg/kg) (P)	1.8	104.4	12.6	14.3
Available Potassium (mg/kg) (K)	4.2	143.1	22.4	17.2
Soil Organic Carbon (%) (SOC)	0.1	1.2	0.7	0.2
$CaCO_3$ (mg/kg)	0.05	10.7	2.1	3.0
Sand (%)	8.3	68.3	40.8	18.4
Silt (%)	7.7	58.0	27.6	14.2
Clay (%)	21.0	63.7	31.8	8.3

Development of prediction models for some soil properties

Stepwise regression analysis was done to all the six spectral data sets for eight soil properties and prediction models were developed. Based on the adjusted R^2 values, most suitable spectral parameter for predicting available soil N is first derivative of absorbance (A'), and for available K, it is the first derivative of reflectance (R'). However, the second derivative of reflectance (R'') was chosen for prediction of available P, $CaCo_3$, and silt content in soil whereas for SOC, sand and clay content it was found to be second derivative of absorbance (A'') as the best suitable parameters. The coefficient of determination (Adjusted R^2) of multivariate regression models has been used for evaluation of models developed with different types of spectral data sets for each selected soil parameter. The adjusted R^2 for all 8 parameters were reasonably high (ranging from 0.65 to 0.87) indicating prediction models from lab spectra were more reliable. However, these R^2 values reduced (ranging from 0.39 to 0.7) when field spectral data were used and reduced further (ranging from 0.28 to 0.52) when Hyperion derived spectral data were used. Comparison of adjusted R^2 of models pertaining to three approaches is given in Figure 4. The laboratory collected data were found to have pure spectral pattern with least noises and high signal to noise ratio compared to other two types of observations hence it yielded reliable prediction models. Being Hyperion sensor at a height of 705 km and having spatial resolution 30 m, it contributes to two major limiting factors for low R^2. One limitation was the atmospheric noise and poor signal to noise ratio compared to spectroradiometer data which scanned the soil at hardly 1 m away. Second limitation is unlike spectroradiometer which scanned the soil very closely covering a few cm^2 areas, satellite spectral records one value for 30 x 30 m^2 area which ignored the spatial variabilities of soil properties. However, some soil properties like SOC, $CaCo_3$ and silt content can be predicted even from Hyperion sensor data with reasonable accuracy ($R^2 > 0.5$; Figure 04).

Validation of the prediction using Hyperion reflectance data for N, P, K and SOC was done using 1/3rd of 85 soil samples which were not used for model development. The comparison was made between the predicted and measured values for each soil property drawing 1:1 line as shown in Figure 5.

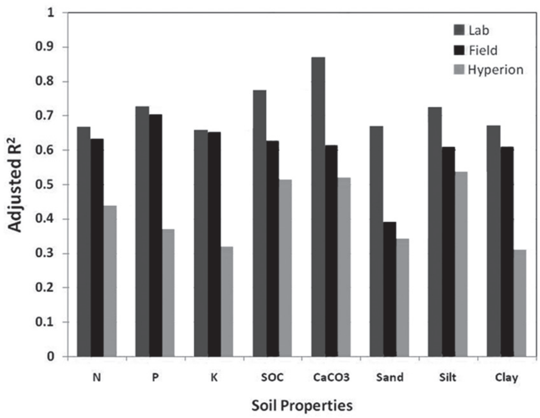

Figure 4. Comparison of adjusted R^2 of prediction models developed from laboratory, field and Hyperion models

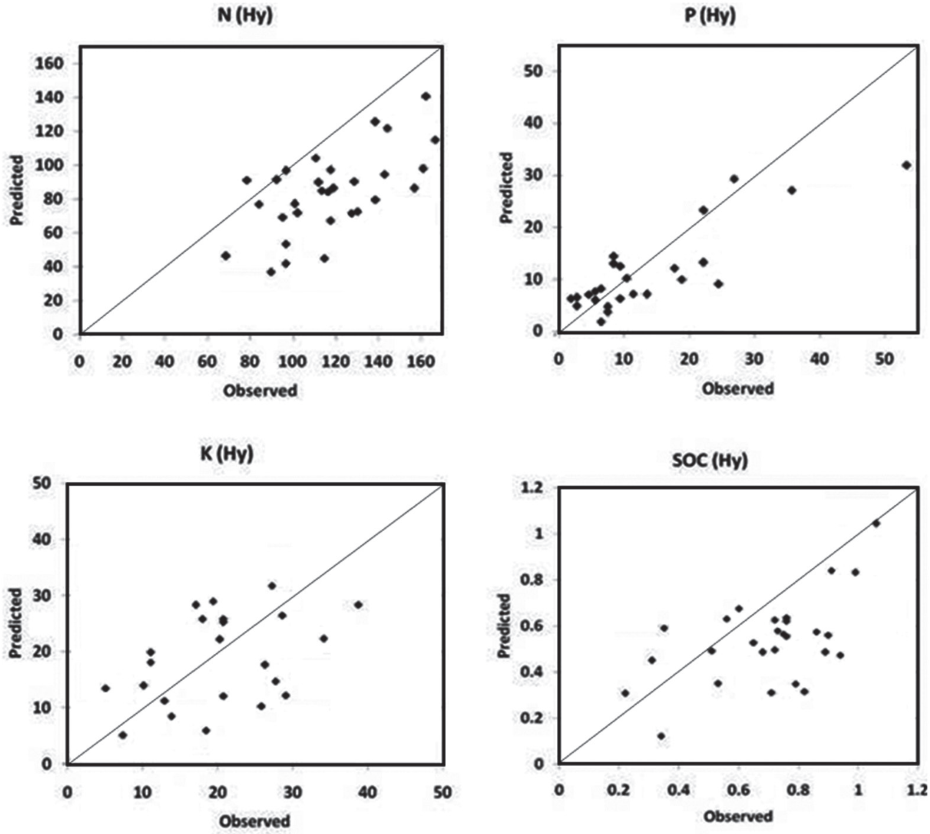

Figure 5. Comparison of Hyperion predicted and observed N, P, K and SOC

Conclusion

This study aimed at evaluating applicability of satellite images for predicting soil properties and compared with soil properties predicted using proximal sensing approaches and observed values. The study found that the Hyperion satellite data was comparable with ground spectral observations after atmospheric correction using ENVI-FLAASH algorithm. Stepwise regression analysis with derived spectral parameters such as first and second derivative of reflectance and absorbance were found better for soil parameter estimation than original reflectance or absorbance data sets irrespective of the platform of the sensor. Model predictability as expressed by R^2 revealed that stepwise regression analysis was better for soil property prediction with derived spectral data sets than original reflectance data sets. Although the model predictability of Hyperion reflectance data is lower than that of field and laboratory measured reflectance, out of 8 soil parameters (SOC, $CaCo_3$, N, P, K, sand, silt and clay), some soil properties like silt, SOC, $CaCo_3$ and silt content could still be predicted with reasonably good accuracy ($R^2>0.5$) with Hyperion satellite data.

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