Review of preprocessing techniques used in soil property prediction from hyperspectral data

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Abstract: Soil properties are neither static nor homogenous with space and time. Capturing the spatial variation of soil properties through conventional methods is a difficult task. Hyperspectral remote sensing data provide rich source of information produced in the form of spectrum at each pixel which can be used to identify surface materials. Airborne and spaceborne narrowband hyperspectral sensors have come to the fore which provides spectral information across large area. Thus, it is a promising tool for studying soil properties and can be used as an alternative to conventional method. But atmospheric attenuation and low signal to noise ratio are major problems with this type of data. Preprocessing of hyperspectral airborne/spaceborne data is required to extract soil properties. This paper reviews previous studies on prediction of soil properties from hyperspectral airborne and satellite data during the past years and the preprocessing techniques used in these predictions.

1. Introduction
Remotely sensed hyperspectral satellite data have great potential for quantitative assessment of soil and vegetation parameter at spatial scale. The development of methods to map soil properties using optical remote sensing data in combination with field measurements has been the objective of several studies during the last decade (Ben-Dor et al., 2009). Also it has been a challenge to find the most appropriate technique for studying soil properties from optical data and thus reducing the time and effort involved in field sampling and laboratory analysis.

Soil reflectance in the visible near-infrared and mid-infrared regions has been widely used in many studies. Some of the soil properties predicted from reflectance data were organic matter (OM), soil

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Our group works on application of Hyperspectral data for soil and vegetation discrimination applications. In the process of applying this data to any application, major issue to be addressed is to account for the effects of atmosphere on the hyperspectral data and to account for it appropriately. Though there are several algorithms available to address this, there is no guideline on the application of them. One of the issues that we wish to address is how best to account for the effect of atmosphere so that proper signal of the targets is extracted for further analysis.

PUBLIC INTEREST STATEMENT
The present review paper would be very useful in the process of digital soil mapping mission from satellite data. As soil is a precious non-renewable resource, it has to be examined periodically. Prediction from satellite data provides a continuous method of monitoring soil quality. The accuracy of prediction depends on the quality of satellite data. The methods to improve quality of data are reviewed in this paper.
organic carbon (SOC), total nitrogen (TN), pH, moisture content (MC), electrical conductivity (EC), phosphorous (P), potassium (K), calcium (Ca), magnesium (Mg), sodium (Na), manganese (Mn), zinc (Zn), and iron (Fe) with various levels of prediction accuracy. Various prediction models such as multiple linear regression (MLR), principal components regression (PCR), stepwise multiple linear regression (SMLR), partial least squares regression (PLSR), artificial neural networks (ANN), etc. were used. These models work well with signals obtained under laboratory conditions, with minimal source of noise. Thus, performance of these models on remotely sensed airborne or spaceborne data is influenced by atmospheric interference and the occurrence of spectral noises. At this juncture, the role of preprocessing techniques on the prediction accuracy of soil properties from remotely sensed data needs to be studied.

Preprocessing techniques consist of atmospheric correction algorithms as well as spectral pretreatment and smoothing methods. Over the years, atmospheric correction algorithms have evolved from applied math approach to ways supported on rigorous radiative transfer (RT) modeling (Minu & Shetty, 2015). Noise and unwanted spectral signals are removed by spectral pretreatment and smoothing methods. Only good-quality data with better signal-to-noise ratios can be conveniently used for the purpose.

Minu and Shetty (2015) review different hyperspectral atmospheric correction algorithms developed during the past years. Internal average reflectance approach (Kruse, Raines, & Watson, 1985), flat field approach (Roberts, Yamaguchi, & Lyon, 1986), empirical line (EL) method (Roberts, Yamaguchi, & Lyon, 1985), QUIck atmospheric correction (Bernstein et al., 2005) etc. are empirical or semi-empirical atmospheric correction methods. RT codes try to simulate the transfer process of an electromagnetic wave in the atmosphere. The normally used RT codes are LOWTRAN (Kneizys et al., 1988), MODTRAN (Berk, Bernstein, & Robertson, 1989), 5S (Tanré, Deroo, Duhaut, Herman, & Morcrette, 1990), and 6S (Vermote et al., 1997). There are a range of software programs available to model the atmosphere including ATmospheric REMoval algorithm (ATREM) (Gao, Heidebrecht, & Goetz, 1993), ATmospheric CORrection (ATCOR) (Richter, 1996), Fast Line-of-sight Atmospheric Analysis of Spectral Hypercubes (FLAASH) (Adler-Golden et al., 1998), Imaging Spectrometer Data Analysis System (ISDAS) (Staenz, Szeredi, & Schwarz, 1998), High-accuracy ATmosphere Correction for Hyperspectral data (HATCH) (Qu, Goetz, & Heidbrecht, 2001), Atmospheric CORrection Now (ACORN) (ACORN 4.0, 2002) etc. Hybrid methods include combinations of empirical approaches and radiative modeling for the derivation of surface reflectance from hyperspectral imaging data. Each preprocessing technique is made of its own assumptions. So there is a need to analyze limitations of different preprocessing techniques and to come up with a universal method.

2. Prediction of soil properties from airborne/spaceborne hyperspectral data

Hyperspectral sensors operate with more than hundreds of bands with good spatial and spectral resolution producing continuous spectra. With the progress and maturity of technology, hyperspectral remote sensing has found a wide range of applications in mapping soil types and quantifying soil constituents. Review papers by Ben-Dor et al. (2009); Ge, Thomasson, and Sui (2011); Mulder, de Bruin, Schaepman, and Mayr (2011), etc. point toward it. Airborne sensors provide high spatial resolution (2–20 m), high spectral resolution (10–20 nm), and high SNR (>500:1) data. Even though satellite hyperspectral imageries have become available since 2000, only few attempts have been made to use them for mapping soil properties. This may be due to their low signal to noise ratio. Tables 1 and 2 summarize previous studies carried out using airborne and satellite hyperspectral imageries to predict soil properties. The preprocessing techniques used are also mentioned in the table.

It is seen that RT models are mainly used in preprocessing of airborne imagery. It may be due to the fact that more information on atmospheric conditions are available in the case of airborne sensors, so that modeling of atmosphere can be done precisely and it can be removed to obtain pure signal. Whereas semi-empirical models like FLAASH are mainly used in hyperspectral imageries. Comparison of different models are still lacking in this field. Also EL method which also requires ground information gives good results. But it is limited only to the areas where ground information
| Soil property | Platform/spectral range/spatial resolution | Field nature | Country | Preprocessing method | Prediction tech. | \( R^2 \) value | Author |
|---------------|-----------------------------------------|--------------|---------|----------------------|-----------------|-----------------|--------|
| Fe            | AVIRIS (400–2,500 nm) (20 m)            | Pasture and seasonal crops | Brazil | MODTRAN-based (Green, Conel, & Roberts, 1993) | Regression equations | 0.83 | Galvão, Pizarro, and Epiphanio (2001) |
| TiO₂          |                                        |              |         |                      |                 | 0.74 |                     |
| Al₂O₃         |                                        |              |         |                      |                 | 0.68 |                     |
| OM            | DAIS-7915 (400–2,500 nm) (5 m)          | Agriculture fields | Israel | Minimum noise fraction (MNF) (Green, Berman, Switzer, & Craig 1988) for noise reduction; EL technique | Visible and NIR analysis | 0.827 | Ben-Dor, Petkin, Banin, and Karnieli (2002) |
| EC            |                                        |              |         |                      |                 | 0.647 |                     |
| EC pH         |                                        |              |         |                      |                 | 0.665 |                     |
| Mg            |                                        |              |         |                      |                 | 0.67 |                     |
| K             |                                        |              |         |                      |                 | 0.59 |                     |
| OM            |                                      |              |         |                      |                 | 0.55 |                     |
| OM TiO₂       |                                      |              |         |                      |                 | 0.74 |                     |
| OM Al₂O₃      |                                      |              |         |                      |                 | 0.68 |                     |
| OM pH         |                                      |              |         |                      |                 | 0.67 |                     |
| OM Mg         |                                      |              |         |                      |                 | 0.59 |                     |
| EC pH         |                                      |              |         |                      |                 | 0.665 |                     |
| Mg OM Al₂O₃  |                                      |              |         |                      |                 | 0.67 |                     |
| K OM TiO₂     |                                      |              |         |                      |                 | 0.59 |                     |
| Iron oxide    | CASI-A (400–1,000 nm) (3 m)            | Sand dunes   | Israel | EL technique | Spectral indices based model | 0.59 | Ben-Dor et al. (2006) |
| Gravel coverage % | DAIS-7915 (400–2,500 nm) (5 m) | Alluvial fan | Negev desert, Israel | MNF technique for noise reduction and EL technique | Ferric absorption feature depth(AFD) model | 0.83 | Crouvi, Ben-Dor, Beyth, Avigad, and Amit (2006) |
| SOC           | HyMap (450–2,500 nm) (3.5 m)           | Agriculture fields | Germany | ATCOR Richter & Schläpfer, (2002); Schläpfer & Richter, 2002 | MLR | 0.9 | Selige, Böhner, and Schmidhalter (2006) |
| TN Sand Clay  |                                        |              |         |                      |                 | 0.92 |                     |
| SOC TN Sand Clay |                                      |              |         |                      |                 | 0.95 |                     |
| SOC TN Sand Clay |                                  |              |         |                      |                 | 0.71 |                     |
| EC pH         |                                      |              |         |                      |                 | 0.86 |                     |
| Mg Na Cl      |                                      |              |         |                      |                 | 0.87 |                     |
| Cl            |                                      |              |         |                      |                 | 0.65 |                     |
| EC pH         |                                      |              |         |                      |                 | 0.86 |                     |
| Mg Na Cl      |                                      |              |         |                      |                 | 0.86 |                     |
| Clay          |                                      |              |         |                      |                 | 0.65 |                     |
| EC pH         |                                      |              |         |                      |                 | 0.86 |                     |
| Mg Na Cl      |                                      |              |         |                      |                 | 0.86 |                     |
| Clay          |                                      |              |         |                      |                 | 0.65 |                     |
| Ca CO₃         |                                      |              |         |                      |                 | 0.6696 |                     |
| Cl            |                                      |              |         |                      |                 | 0.6188 |                     |
| Mg Na Cl      |                                      |              |         |                      |                 | 0.6188 |                     |
| Clay          |                                      |              |         |                      |                 | 0.6224 |                     |
| CaCO₃         |                                      |              |         |                      |                 | 0.7376 |                     |
| Clay          |                                      |              |         |                      |                 | 0.7376 |                     |
| CaCO₃         |                                      |              |         |                      |                 | 0.7376 |                     |

(Continued)
is available. Also it is seen that prediction of SOC gives good results compared to other properties. This may be because the soil reflectance curve is affected more by presence of OM.

3. Inference
Several surface soil properties were modeled from remotely sensed hyperspectral imagery. Since soil is a more heterogeneous material, more careful spectral manipulations need to be done in assessing its properties from spectral data. For the best performance of any prediction system, the key influencing factors are to be identified and optimized. Although there are many soil properties prediction models, the prediction accuracy is found to be still very low.

The noises should be removed from the hyperspectral imagery in order to utilize it to the best. The signal to noise ratio should be maximum. Several spectral pre-processing methods are employed in various studies to improve the performance and robustness of the prediction models. Even though the pre-processing techniques affect the prediction model considerably, it was not given that much importance. So to develop a good model there is a need to perform a better preprocessing. In this percept, different preprocessing techniques used in various studies are listed in this review paper. Hybrid methods which combine physical model and image statistics need to be promoted. There is a need to give guidelines on selection of suitable preprocessing technique for the prediction of soil chemical properties.

| Soil property | Platform/ spectral range/spatial resolution | Field nature | Country | Preprocessing method | Prediction tech. | $R^2$ value | Author |
|---------------|-------------------------------------------|--------------|---------|----------------------|------------------|-------------|--------|
| MC            | HyMap (440–2,470 nm) (4 m)                 | Sandy substrates and low vegetation cover area | Germany | MODTRAN4 based ACUM algorithm | Normalized soil moisture index (NSMI) model | 0.819 | Haubrock, Chabrilat, Kuhnert, Hostert, and Kaufmann (2008) |
| Clay          | HYMAP (400–2,500 nm) (5 m)                 | Area is devoted to vineyards | France | ATCOR4 code for airborne sensors | Continuum removal analysis | 0.58 | Lagacherie, Baret, Feret, Madeira Netto, and Robbez-Masson (2008) |
| CaCO$_3$      |                                          |              |         |                      |                  | 0.47 |        |
| SOC           | AHS-160 sensor (430 nm–2,540 nm) (2.6 m)  | Agriculture fields | Belgium | MODTRAN 4 embedded with ATCOR 4 (Richter, Schläpfer, & Müller, 2006) | PLSR | RPD = 1.47 | Stevens et al. (2008) |
| Clay          | HYMAP (400–2,500 nm) (5 m)                 | Area is devoted to vineyards | France | ATCOR4 code for airborne sensors | PLSR | 0.64 | Lagacherie, Gomez, Bailly, Baret, and Coulouma (2010) |
| CaCO$_3$      |                                          |              |         |                      |                  | 0.77 |        |
| SOC           | AHS-160 sensor (430 nm–2,540 nm) (2.6 m)  | Cropland | Luxembourg | MODTRAN4-based algorithm; (Richter, 2005; Rodger & Lynch, 2001) | PLSR | 0.71 | Stevens et al. (2010) |
| C             | HyperSpecTIR (400–2,450 nm) (2.5 m)        | Tilled agricultural fields | MD, USA | Imagery processing by ENVI 4.7; & different signal smoothening methods | PLSR | 0.65 | Hively et al. (2011) |
| Al            |                                          |              |         |                      |                  | 0.76 |        |
| Fe            |                                          |              |         |                      |                  | 0.75 |        |
| Silt          |                                          |              |         |                      |                  | 0.79 |        |
| Clay          | MIVIS (430–1,270 nm) (4.8 m)              | Maize field, but the crop had not emerged | Central Italy | MODTRAN4-based model (Vermote, Tanre, Deuze, Herman, & Marcotte, 1997) | PLSR | 0.78 | Casa, Castaldi, Pascucci, Palombo, and Pignatti (2013) |
| Silt          |                                          |              |         |                      |                  | 0.56 |        |
| Sand          |                                          |              |         |                      |                  | 0.81 |        |
| SOC           | CASI 1500 (380–1,050 nm) (0.2 m)          | Compost added soil | Italy | EL calibration with asphalt spectral signatures | Correlation between the second derivative value and SOC | 0.85 | Matarrese et al. (2014) |
Table 2. Summary of soil properties prediction using satellite remote sensing techniques

| Soil Prop | Platform | Field characteristics | Country | Preprocessing method | Prediction tech. | $R^2$ values | Author |
|-----------|----------|-----------------------|---------|----------------------|------------------|--------------|--------|
| SOC       | EO1 Hyperion (400–2,500 nm) (30 m) | Cotton crops and pasture. Field size = 100 × 500 m$^2$ | Australia | Algorithm based on ATREM and SS code. | PLSR | 0.5 | Gomez, Viscarra Rossel, and McBretney (2008) |
| OM        | EO1 Hyperion (400–2,500 nm) (30 m) | Raw-crop agriculture field | Central Indiana, USA | ENVI FLAASH module | PLSR | 0.74 | Zheng (2008) |
| TN        | EO1 Hyperion (400–2,500 nm) (30 m) | Arid regions; 4,332 km$^2$. | Shanxi, China | EL atmospheric correction | Linear regression model | 0.84 | Wu, Liu, Chen, Wang, and Chai (2009) |
| TP        | EO1 Hyperion (400–2,500 nm) (30 m) | Bare field | Central Indiana, USA | ACORN | PLSR | 0.79 | Zhang, Li, and Zheng (2009) |
| TC        | EO1 Hyperion (400–2,500 nm) (30 m) | Agriculture–pasture mixed area. | Hengshun County, China | Internal average relative reflectance | Land degradation spectral response units (DSRU) model | 0.722 | Wang, He, Lv, Chen, and Jian (2010) |
| Clay      | EO1 Hyperion (400–2,500 nm) (30 m) | Maize field, but the crop had not emerged, 12 and 17 ha plots | Central Italy | FLAASH | PLSR | 0.6 | Casa et al. (2013) |
| Silt      | CHRIS-PROBA (415–1,050 nm) (17 m) | Wheat and potato fields. Field size = 90 × 90 m$^2$. | China | FLAASH | PLSR | 0.63 | Lu, Wang, Niu, Li, and Zhang (2013) |
| Sand      | EUR image (17 m) | Scattered paddy fields, 47 km$^2$. | Karnataka India | FLAASH, Moving average Savitzky–Golay | PLSR | 0.63 | Gopal, Shetty, and Ramya (2014) |
| OM        | EO1 Hyperion (400–2,500 nm) (30 m) | Coastal soils densely covered with vegetation | Florida, USA | FLAASH, MNF filter | PLSR | 0.67 | Anne, Abd-Ellahman, Lewis, and Hewitt (2014) |
| POM       | EO1 Hyperion (400–2,500 nm) (30 m) | | | | | | |
| MAOM      | EO1 Hyperion (400–2,500 nm) (30 m) | | | | | | |
| labile C  | EO1 Hyperion (400–2,500 nm) (30 m) | | | | | | |
| labile N  | EO1 Hyperion (400–2,500 nm) (30 m) | | | | | | |

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