
The spectral response characteristics of the soils and their possible estimation by using partial least square regression (PLSR) analysis

Zelikman. E, Carmina. E

Department of Geography and the Human Environment, Tel-Aviv University, Ramat Aviv,
Tel-Aviv 69978, Israel
eugenyzel@gmail.com

ABSTRACT

The objective of this study was to investigate the potential of diffuse reflectance spectroscopy technique to predict several important soil parameters such as soil moisture (SM), hygroscopic water (HW), soil carbonates (SC) and specific surface area (SSA) through descending layers of the soil stratigraphy. For these purposes a field spectrometer (Analytical Spectral Device, ASD) with a probe (sub-surface spectral head device - 3S-HeD) for reading subsoil reflectance data were used. 145 samples, taken from different Israeli soils at different depth and a spectral library containing laboratory and field in-situ collected spectra (by using 3S-HeD device) were used to generate calibration and validation models in the study based on the Near Infrared Analysis (NIRs). These models were generated by the correlation between spectral characteristics and chemical soil properties separately for each soil property, using partial least square regression (PLSR) analysis. The regression coefficients between measured and predicted values of the soil properties varied between 0.93 and 0.99 in the calibration and validation stages, RMSE (Root Mean Square Error) between 0.09 and 4.6, which showed that NIRS method had potential to accurately predict these attributes in soils. Even though the prediction results for SSA are relatively poor (RMSE varied between 27 and 30) accurate linear relationships between the laboratory measured and predicted values exist (it is seen by high correlation r values in the calibration and validation stages). In addition, to predict studied properties down the profile by using 3S -HD device, eighteen drill holes locations were selected from the surface IS-based map within the semi-arid agricultural area, using clustering isodata methods. For each drill holes ten layers were spectrally measured down to 100 cm depth. The results we got from the spectroscopic analysis were logical given the environmental conditions. Further research is needed to compare our results with chemical lab tests of the same soil samples, and to repeat this study in other locations. This new approach is worth investing in as it is cost effective for such a variety of applications currently required.

Keywords: Spectral response, SSA, PLSR, POS, models.

Notations

SEP is the standard error of prediction; y is the predicted value of a soil property; x is the measured value of the same soil property, and n is the total number of samples.

1. Introduction

Spectral assessment of soils, using ground based optical sensors, is actually widely accepted as an alternative to conventional methods of soil survey. Known soil attributes absorb and reflect incident radiation at discreet levels. The differences between the levels of both absorption and reflection at each wavelength, create various structural configurations in the

spectral signature, such as troughs and peaks or reflectance inflection differences (RIDs- Nanni and Dematte, 2006), whose positions correspond to specific chemical groups. An intercorrelation between featureless and constituents with spectral features is the mechanism by which those harder to detect constituents are recognized and measured. Until now such work was based on laboratory measurements of spectra and building of NIRS models used to successfully assess many important characteristics of soils, both at the surface level (Dalal and Henry, 1986; Morra et al., 1991; Chang et al., 2001; Cozzolino and Moron, 2003; and many other) and later down the soil profiles (Galvao et al., 1997; Dematte, 2002; Dematte et al., 2004). However, only some information is available for the use of Diffuse Reflectance Spectroscopy (DRS) for in situ analysis of soil properties. It is known some soil on-the-go mobile systems (e.g. Bricklemeyer and Brown, 2010; Christy, 2008; Waiser et al., 2007) and static proximal soil sensing (Kusumo et al., 2011; Rossel et al., 2006). Subsurface soil spectroscopy, with an emphasis on stratigraphy in situ, has rarely been researched, and there is minimal previous data to study. Ben-Dor et al. (2008) developed an accessory (3S- HeD) that can be attached to a VNIR portable optic spectrometer to measure soil spectra whereby the optical head penetrates the soil profile. We present a study on ground-based approaches, based on the Penetrating Optical Sensor (POS) technology. A practical difficulty this technique faces is that soils in the field, unlike used in the laboratory are generally moist and have uneven surfaces (Wu Chun-Yu et al., 2009). However, it is known that in situ soil reflectance measurements combined with locally calibrated empirical models should prove a valuable and efficient tool for rapidly approximating soil properties. It was found, for example, that ground-based spectrometers give RMSE of cross-validation similar to the limit of repeatability of a routine soil organic carbon (SOC) analytical technique (Stevens et al., 2008). Viscaria Rossel et al. (2009) noted that predictions of clay content from the field-collected spectra (RMSE=7.9%) were slightly more accurate than those from the laboratory-collected spectra (RMSE=8.3%) and stated improving the capacity of the models by extending the range of the PLSR calibrations by “spiking” them with 74 field spectra.

It is known, that Imaging Spectroscopy (IS) data have a number of disadvantages relative to point spectrometry (low signal-to-noise ratio, significant atmosphere attenuation, proper data, and so on). Soil profiling is the ultimate parameter for soil classification since the sun's radiation interacts with only the upper layer of the soil surface. However, IS allows every pixel in the image to be shown as a reflectance spectrum, and to obtain high spatial resolution, which may indicate the need to investigate different ways of using the IS data for soil analysis, for example, choosing locations to sample the soil profile.

Use of the spectral - based technology for the soil evaluation and mapping highly appropriate and important in Israel, because continuous replenishment of practically all soils in the Mediterranean area with aeolian material, which is transported from the Sahara Desert, affects the generic structure and heterogeneity of soils (Yaalon and Canor, 1973; Simonson, 1995). Under such conditions, it is often difficult to get a realistic picture of the vertical and horizontal distribution of soil properties, using traditional methods.

The ultimate goal of our research is to enable the use of appropriate technology for practical applications in soil classification and mapping.

The main goals at this stage of the research are:

1. Tested the accuracy of a models for predictions of the above mentioned parameters using a spectral library that contains spectra collected in the laboratory from air-dry

ground soil but also a number of spectra that were collected in situ at field conditions on the depth, using PLSR analysis.

2. Use the built models to predict soil properties for independent agricultural area in the semi-arid zone for the entire soil profile by using POS technology.

2. Materials and methods

2.1 Soil sampling

Soil samples, taken from different Israeli soils were used to generate predictive models based on the NIRs approach. 90 samples were taken from an existing Israeli soil bank (Ben-Dor and Banin, 1995a, 1995b) and 55 were taken from the more recently drilled holes. The soil bank samples were created by sampling the upper 0 to 5 cm of the soil profile. The drill holes were excavated by using a 10-cm Dutch driller, and then samples were taken every 10cm down to 100cm. Each sample was placed into a sealed plastic bag and sent to the laboratory for analysis.

2.2 Spectral analysis

All samples of Israeli soils, used for models creation, were spectrally measured by employing the field spectrometer ASD and using the High Intensity Contact Probe (Ben-Dor et al., 2008). Before measurement big stones and plant residue were excluded from the samples. Then the soil was shaken and pressed gently before levelling with a spatula for a better light reflection and high signal to noise ratio. For each sample, two spectral measurements were averaged. The same ASD spectrometer with a probe 3S-HD was used for the drill holes measurements in situ on the depth. To predict soil properties 190 spectra characterizing soil profiles of 19 drill holes have been measured within the independent semi-arid area.

2.3 Field spectral measurements

The on-the-go measurement system was used. Detailed information about this system can be found in Ben-Dor et al. (2008). Figure 1 shows a general view of the device. The device is hooked to an ASD field spectrometer that is sensitive to the VNIR-SWIR spectral region (350-2500 nm). After the holes were bored, the instrument was calibrated according to the halon standard. Then the instrument probe was lowered into the hole, and measurements were taken at intervals of 10 vertical cm, down to 100cm at the deepest point. The cylindrical nature of the bore holes necessitates an averaging of the wall's values at each depth. The sensor's field of view is a 90° swath of the wall. By rotating the sensor, four of these measurements were taken at each depth in order to get the full 360 degree view of the wall, and then they were averaged out to a single value for each depth.

2.4 Chemical

Four examined soil properties were quantified. The soil moisture (SM) and hygroscopic water (HW) were determined by using the oven-drying method (Gardner, 1986), the soil carbonate (SC) was determined by using the calcimeter method (Nelson, 1986), the specific soil area (SSA) was determined by using the ethylene glycol monoethyl ether method (Thomas, 1986). Hygroscopic water is the most important spectral feature used in the identification of SSA, which is highly correlated with the properties of various Israeli soils,

such as clay content (Banin and Amiel, 1970). Before each laboratory measurement, a gentle grinding process took place to attain a 2-mm grain-size fraction in each sample.



Figure 1: 3S- HeD assembly.

2.5 Spectral-based models creation

By comparing the reflectance measurements to their equivalent wet chemistry measurements, multivariate models were constructed and tested to predict each soil property based solely on the spectral measurement. Partial least square regression (PLSR) was used to relate reflectance spectra with measured soil properties. is an example of a latent variable regression method (Martens and Naes, 1987), where PLS components known as factors are selected to maximize both description of the independent variables and correlation to the dependent variables. To develop the statistical model of each soil property, the total samples were randomly divided into two sets. One set was used to develop a prediction equation (calibration set), and the other set was used to validate the predictive against unknown samples (validation set). The multivariate calibration models were calculated by PLSR using Unscrambler 9.1 software (Esbensen, 2002). Various spectral pretreatment manipulations to minimize spectral side effects were applied. The PLS analysis was applied to the reflectance, and to the 1st and the 2nd derivatives of the reflectance (Savitzky and Golay, 1964). This process amplifies the “peakedness,” which is considered advantageous for noisy and scattered data.

The ability of the reflectance technique to predict a soil property was evaluated by the lowest standard error of prediction (SEP), the lowest root mean square error of prediction (RMSEP), and the highest coefficient of correlation (r). SEP is the standard deviation of the difference between the measured and the estimated values for samples in the validation set and were calculated from the following equation:

$$SEP = \left[\sum (y - x)^2 / n - 1 \right]^{1/2} \quad (1)$$

where y is the predicted value of a soil property estimated using the NIRS technique, x is the measured value of the same soil property by standard laboratory method and n is the total number of samples.

The RMSEP is the square root of the residual y variance divided by n, expressed in the original measurement unit. Thereafter all models is used to predict quantitative parameters of chemical properties for the drill hole samples.

2.6 The study area to predict soil properties

An independent area of about 4 000 m² near Ashdod (in the south of Israel's Coastal Plain) at the boundary of the Nizzanim sand dunes, was selected. The area is a bare agricultural field, where no farming has been done in recent years. Figure 2 show the location of the research area.

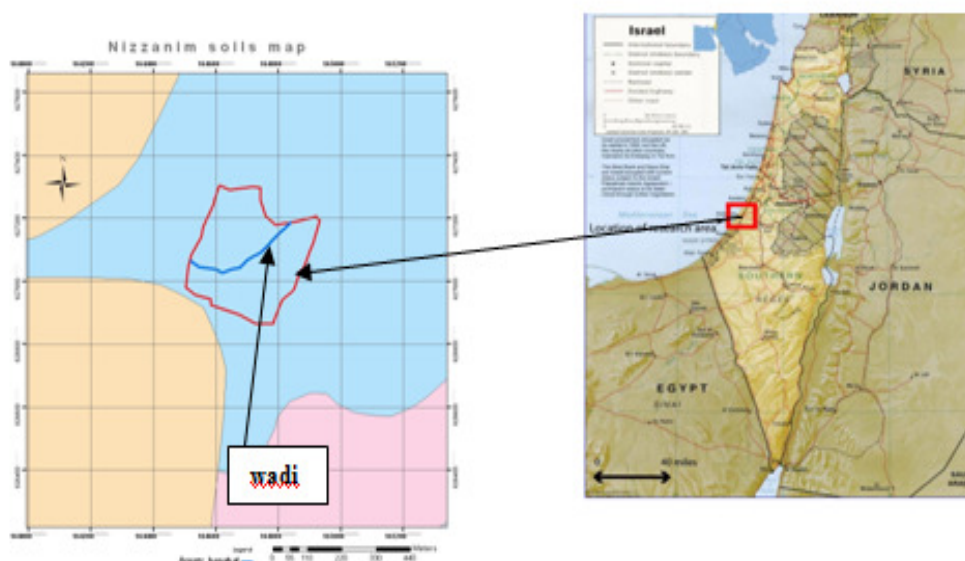


Figure 2: The location (Detailed relief and political map of Israel. <http://www.vidiani.com>) and a schematic soil map of the study area showing geographical coordinates.

At the selected locations, the climate is semiarid with an annual precipitation of about 350 - 400mm. Alluvial Light Brown soils (hereinafter Brown soils) according to the local Israeli system are created within the upper slopes and the flat areas, and these soils exhibit the characteristic properties of semi-arid climate soils, such as increased clay content in median horizons, and fine grain soil saturation with calcium carbonates (Dan and Koyumdjiski, 1979). Similar soils in the FAO classification are Calcic Xerosols and in the American soil taxonomy are Haplargids and Camborthids (Correlation List for the Soils of Israel, 2001).

Found at the bottom of the slope, near the stream in the center of the field (Figure 2) are accumulative soils (Fluvisols in the FAO classification) that developed from alluvial-deluvial sand deposits, and are mixed with loamy deposits during the erosion process (hereinafter Alluvial soils). Dense clay deposits are transported along the stream, and out towards the sea during the rainy season. Grainy material transported by the offshore winds is mixed with heavy sediments, which probably explains the medium texture of the soil, despite neighboring Nizzanim dunes.

This area was covered by one swath of the airborne imaging spectrometer, AISA-ES, and later using POS soil survey methods.

2.7 Drill hole locations

Nineteen drill hole locations were selected from the surface IS-based map of the area, using one of the unsupervised classification – isodata methods (Tou and Gonzalez, 1974), that best represented the spectral data space (Christy, 2008). The method is based on territorial mapping of spectrally similar areas, which are identifiable because each pixel in the hyperspectral image is represented by a reflectance spectrum. This is useful in choosing locations to sample the soil profile (which is done by inserting the spectrometer into holes as described above). In each group, several points for boring holes were selected. Then the bore hole locations were drilled and sampled using a 10-cm Dutch driller, and the locations were georeferenced using GPS. Also, absolute heights were measured for each point, and the data were used to derive a height map of the study area, using the Kriging method (Figure 3).

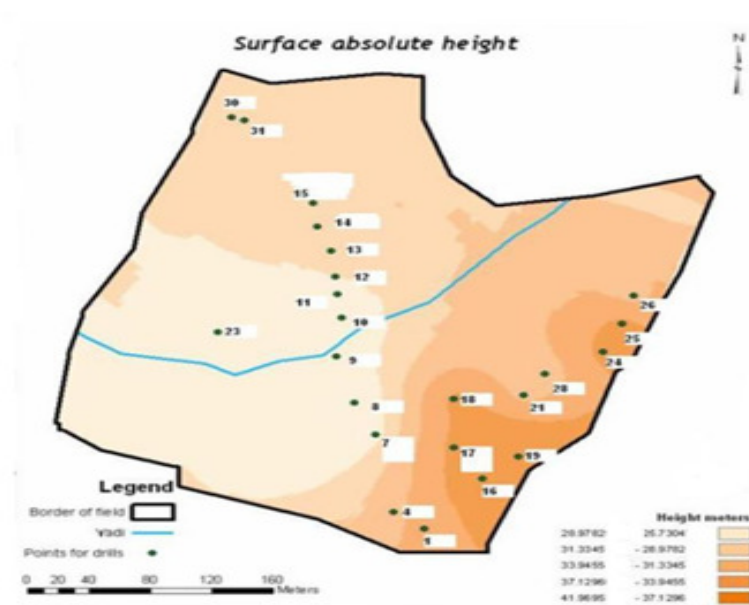


Figure 3: A height map of the study area. Also given are the drilling point position.

Figure 4 shows the isodata classification method applied to hyperspectral images of the studied territory. Six groups of differently colored pixels can be distinguished, suggesting the existence of six different of the topsoil physical and chemical characteristics. It can be seen from Figures 3 and 4 that correlation exists between the spectral characteristics of the topsoil, and the topographies different regions within the study area. Brown soils (for example, holes 17, 18, 19, 24 and 25) which occupy the upper positions correlate, mainly, to the Magenta and Yellow isodata groups. Alluvial soils that accumulate near the stream bed, and correlate to most of the violet colored isodata group. Such difference between soils at different depository levels is similarly observed (for example, holes 21 and 28; holes 19 and 9). But it is necessary to confirm statistically. The POS measurements were carried out in the summer of 2008, by using a 3S-HeD assembly to spectrally interpret the walls of the boreholes. In order to compare and contrast different soils we selected holes in, both, the upper areas and the lower areas at the bottom of slope, and then spectroscopically analyzed the soil profiles to quantify studied soil properties.

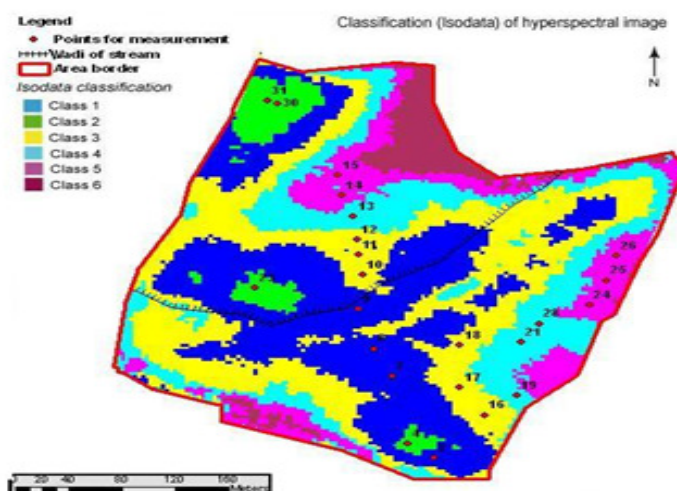


Figure 4: The isodata classification of the area using the IS reflectance image.

2.8 Air-borne data

AISA-ES imaging spectrometer consists of two sensors, measuring along 180 channels (60 in VNIR and 120 in SWIR), in the spectrum of 450-2450 nm. Data was collected at an altitude of approximately 2400m (8000ft) above sea level, with pixel size 1-2 m. After the data acquisition (on November, 2004), raw data were transformed into reflectance, using The Atmospheric CORrection Now (ACORN) and the Empirical line method (ELM). ACORN is a commercially-available, enhanced atmospheric model-based software that uses licensed MODTRAN4 technology to produce high quality surface reflectance without ground measurements (Berk et al, 1999). ACORN uses look-up-tables calculated with the MODTRAN4 radiative transfer code to model atmospheric gas absorption as well as molecular and aerosol scattering effects, converting the calibrated sensor radiance measurements to apparent surface reflectance (AIG, 2001).

ELM assumes there is a linear relationship between raw digital numbers (DNs), or radiance and reflectance spectra of ground targets (Baugh and Groeneveld, 2008). To use ELM, we select two or more homogeneous as possible areas in the scene with different albedos. In situ spectroradiometer measurements of these targets are made on the ground. The in situ and remote sensing-derived spectra are regressed and gain and offset values computed. The gain and offset values are then applied to the remote sensor data on a band by band basis, removing atmospheric attenuation. These data then were used for the selected drill hole locations, using unsupervised classification. We used the technology of the software ENVI to analyze and correct the hyperspectral data, such as a Minimum Noise Fraction (MNF) procedure to noise reduction procedure, and the signal-to-noise ratio (SNR) of the reflectance image.

3. Results and discussion

3.1 Spectral-based models NIRA to predict soil properties

Statistics for predicted SSA, carbonates, hygroscopic water and soil moisture for the validation stage are shown in Figure 5. The R (correlation coefficient), RMSE (root mean square error)

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and SE (standard error) between the predicted and measured value for the calibration and validation sets were used to evaluate the prediction ability of NIR spectroscopy technique (Table 1,2).

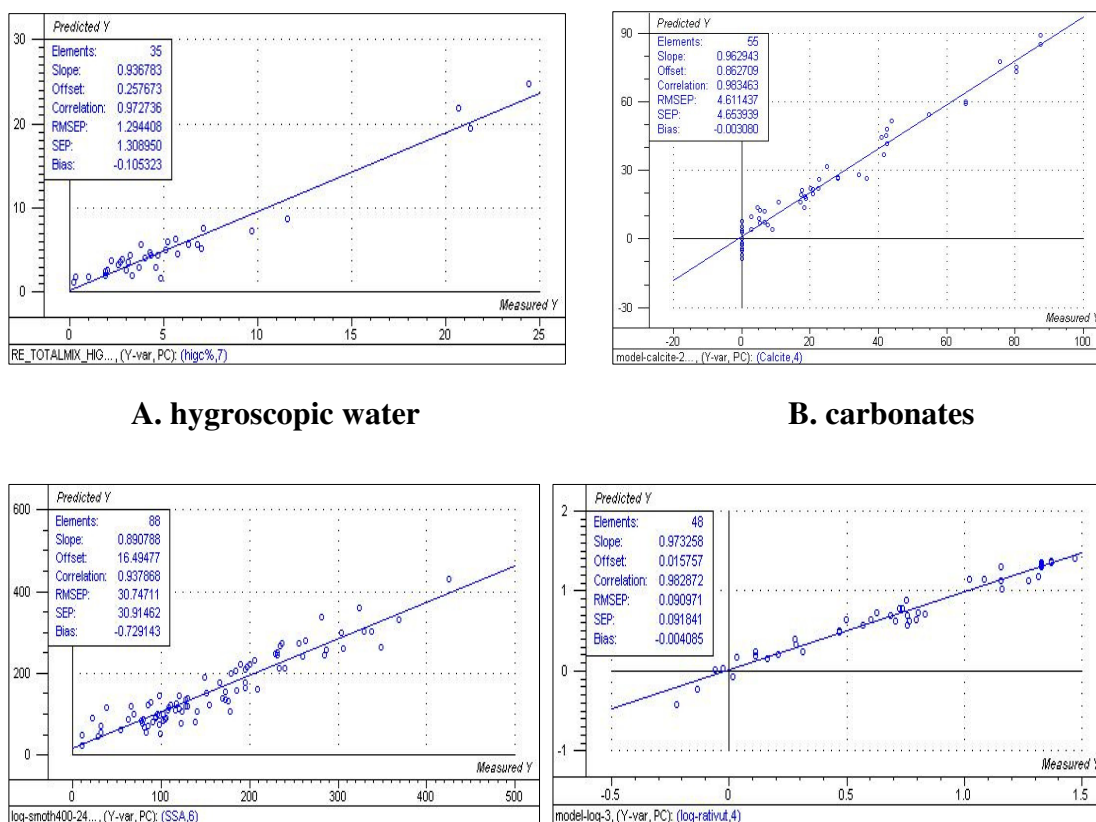


Figure 5: Correlation between measured and predicted values of **A.** hygroscopic water, **B.** carbonates, **C.** SSA and **D.** soil moisture for the validation stage (elements- number of samples; correlation- correlation coefficient; RMSEP- root mean square error of prediction; SEP- standard error of prediction. Also provided bias, offset and slope values).

Table 1: Calibration statistics for studied soil properties

Properties	N samples	R	R ²	SE	RMSE
Hygroscopic water, %	57	0.98	0.96	1.41	1.43
Soil carbonates, %	55	0.99	0.98	3.18	3.15
SSA, m ² /g	88	0.95	0.9	27.3	27.16
Soil moisture, %	48	0.99	0.98	0.07	0.07

Table 2: Validation statistics for studied soil properties

Properties	N samples	R	R ²	SE	RMSE
Hygroscopic water (%)	35	0.97	0.94	1.31	1.29
Soil carbonates (%)	55	0.98	0.96	4.65	4.61
SSA, m ² /g	88	0.94	0.88	30.91	30.74
Soil moisture, %	48	0.98	0.96	0.09	0.09

It can be seen from the tables that the correlation coefficient (r) between measured and predicted values of the studied soil properties in the calibration and validation stages varied between 0.94 and 0.99, coefficient of determination (r^2) between 0.88 and 0.98, RMSE and SE were similar and varied between 0.07- 4.65 which showed that NIRS had potential to accurately predict these attributes in this soil. For SSA values RMSE and SE are higher and varied between 27-30.74, but strong linear relationships between the lab-measured and predicted values exist (indicated by high correlation r values – Figure 5c, Table1).

3.2 Spectral analysis of soils

As discussed, in order to compare different soils, drilled holes were selected in the upper areas and the areas at the bottom, and then spectroscopically analyzed the soil profiles to quantify studied soil properties. Figure 6 shows soil samples taken from within the representative profiles of holes 9 and 19, which were bored into Alluvial and Brown soils, respectively.

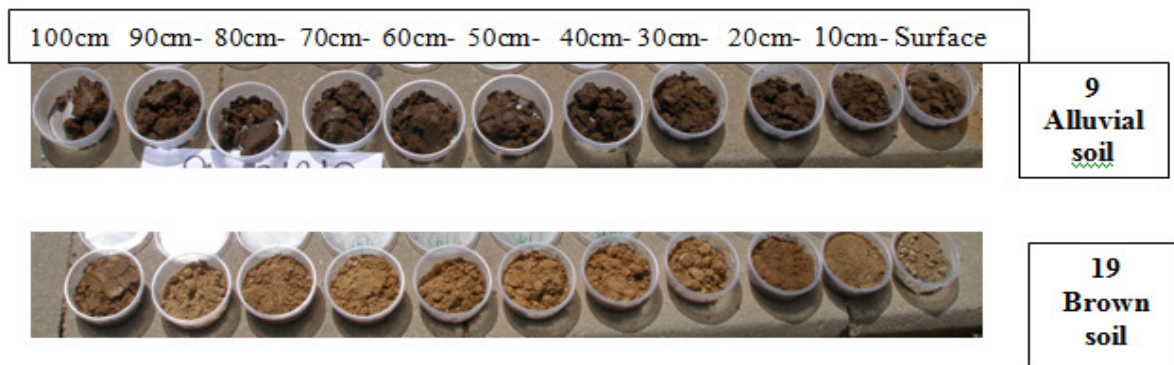


Figure 6: Soil depth samples for selected drill holes: hole 9-Alluvial soil; hole 19- Brown soil.

In Figure 7A and 7B represent averaged reflectance spectra of these soils.

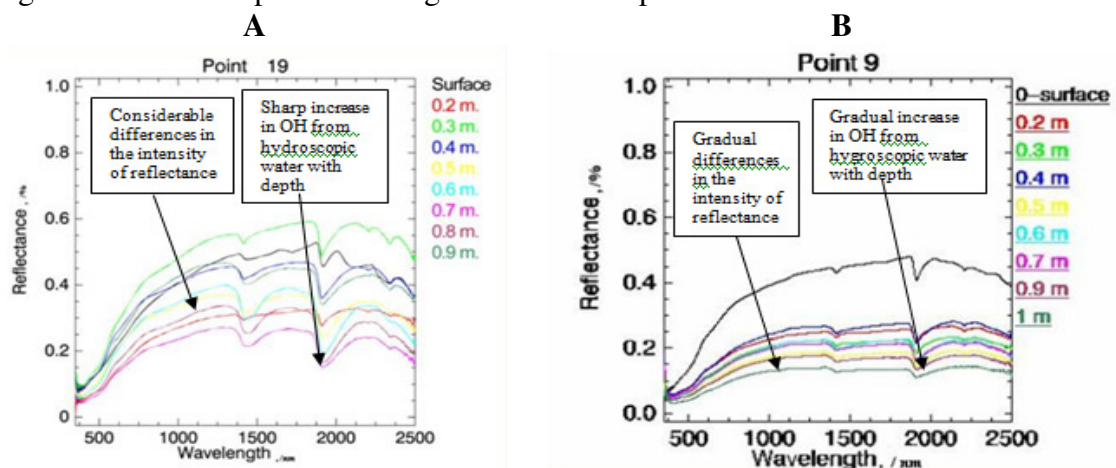


Figure 7: Averaged reflectance spectra on the depth of soils: A. Brown soil; B. Alluvial soil.

As can be seen from Figure 7, both profiles tend to show a decrease in reflectance, with an increase in the width of the spectral concavity at 1400 and 1900nm. This pattern is attributed to OH from the hygroscopic water in the soils (Dematte, 2002). In this case, it clearly indicates that wetter soil horizons correspond with the lowest reflectance values. Close to the

surface, where evaporation is high, all soils have low water content and maximum reflectance, which is characteristic of the top layers of all soils in the area. As can be seen in Figure 7A, the most pronounced hygroscopic water absorption properties for Brown soils, and the lowest reflectance indexes can be observed at 50-80 cm depths, with the maximum occurring at a depth of 70 cm.

Characteristically, alluvial soil (Figure 7B) shows a gradual increase in hygroscopic water absorption properties down the profile, with a maximum occurring at a depth of 100 cm. We observed that soil texture becomes heavier in this layer characteristic. Thus, the changes in reflectance indexes or intensity of reflectance along the soil profile in this case, are related to changes in hygroscopic water content and SSA.

Figure 8 shows the main characteristic spectral signatures and corresponding soil attributes.

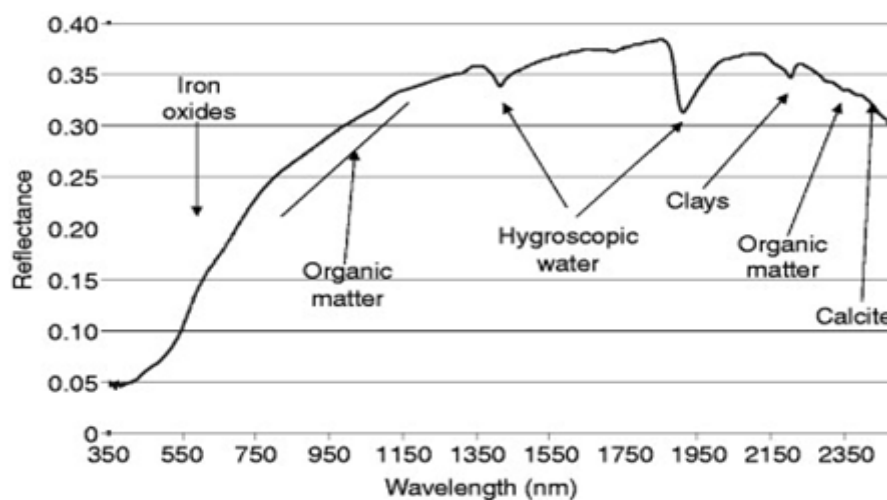


Figure 8: The main characteristic spectral signatures and corresponding soil attributes.

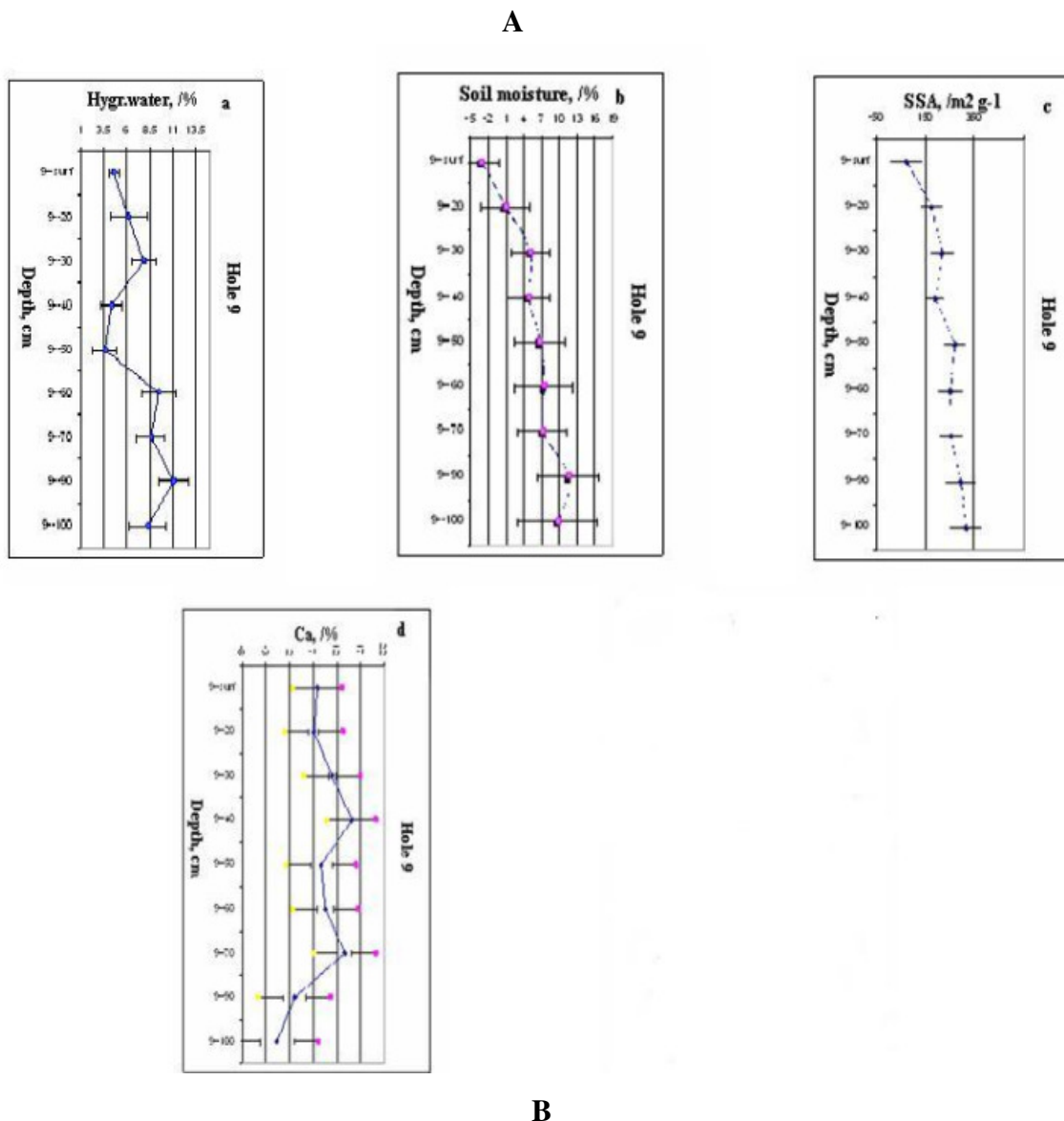
Note the clearly seen spectral feature at 2200 nm in the sampled soils; this feature usually reveals the OH group in the clay minerals lattice. From figure 7A and 7B we observe that the clay mineral peak becomes more symmetrical with an increase in depth (in the horizons where the greatest hygroscopic water contents were observed). This suggests that the major clay mineral is most likely montmorillonite with a small amount of kaolinite (Kruse et al., 1991). This increased SSA is also evident in the correlation between the OH-water absorption features at 1400 and 1900nm and the chemical properties of the SSA. Spectral signatures of carbonates are marked at 2330 nm (Ben-Dor and Banin, 1990) and are visible mostly in the spectra belonging to the Brown soil profile (Figure 8, Figure 7A). It can be seen that there are tendencies common for all soils, such as a strong absorption feature with spectral concavity visible at around 500 nm; this is attributed to iron oxide minerals, such as hematite and goethite (Hunt and Salisbury, 1970). Albedo distribution peculiarities within the profile demonstrate additional soil properties. For example, the relatively high reflectance (up to 40%) of the deeper horizons in the Brown soil stratigraphy, indicate more sandy soil texture. Considerable differences in the intensity of reflectance within these soil profile structures indicate inhomogeneous stratigraphies, (Figure 7A). For Alluvial soils, a sharp decrease in the albedo in subsurface layers with similar reflectance values at all depths bellow the topsoil, correlates with the similarity in color and moisture content indexes at all of those depths (as can be seen from the morphology of the samples in Figure 5). A more continuous spectral

slope across 350-1200 nm, and a small absorption property at 1700 nm at the 70-100 cm horizons indicate a relatively high content of organic matter (Ben-Dor and Banin, 1995a). The absorption feature at about 1300 nm in these soils also indicates the presence of organic matter.

Hence, from the spectra of the Brown soils profile, two main diagnostic indicators can be visually identified: the presence of accumulated clay and of carbonates. The first is related to higher moisture absorption properties in the 50-80 cm depth layer, which determines higher clay content, and can be seen via its correlation with OH-water absorption at 1400 and 1900 nm. The second is related to the carbonates absorption feature at 2330 nm. Also, albedo distribution characteristics expose soil properties that are important diagnostic indicators.

3.3 Predicted soil profiles

Figure 9A and B present the distribution of predicted parameters (hygroscopic water, soil moisture, SSA, and carbonates) that were obtained from the models (applied to the soil in profiles 9 and 19).



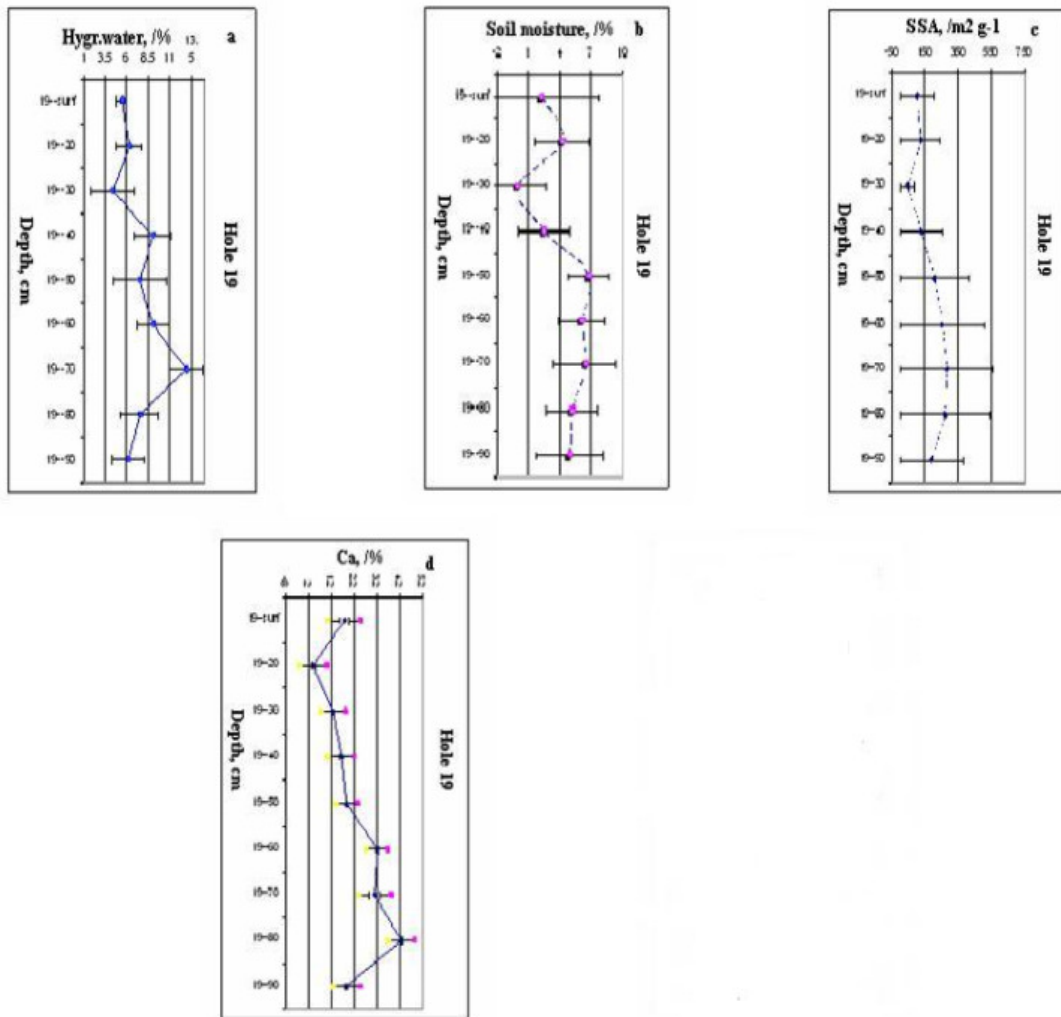


Figure 9: The distribution of predicted quantitative parameters (a. hygroscopic water, b. soil moisture, c. SSA, and d. carbonates) that were obtained from the model as applied to the Alluvial soil in profile 9 (A) and Brown soil in profile 19 (B).

The figures show that hygroscopic water and soil moisture values are predicted by the model to be distributed throughout the profile in the same pattern that they are distributed in, as observed by the spectral data. Therefore, the spectral distribution for alluvial soils correlates to values for hygroscopic water and soil moisture, which increase with depth (Figure 9 A: a, b). Similar profile distributions for hygroscopic water and soil moisture, visible in the Figures, show that at low relative humidity, moisture consists mainly of absorbed water. As would be expected, minimum values are observed on the surface, and values gradually increase with depth, except for an anomaly at the 40 cm and 50 cm horizons, which is clearly visible in the hygroscopic water profile. In the case of both parameters, these values again decrease at the 100 cm layer. These drier bands and the moist layers that they are sandwiched between, are observed using every technique. The properties of soil moisture are most clearly explained by the SSA indicator, showing a gradual increase in clay content with depth (Figure 9A: c). According to the correlation table (Aly et al., 2004) for the SSA indicators, we can say in a certain approximation, that texture in such soils changes roughly from sandy loam on top, to clay, with increasing depth, and have maximum values of 300 and 340 m²/g at 90 cm and 100 cm depths, respectively. This correlates to spectral assessments of

hygroscopic water values. As would be expected, carbonate content proved to be low throughout the whole soil profile, with maximum values at 40 cm depth not exceeding 15% (Figure 9A: d).

In Brown soil, profiles generated by predictive models show that the distributions of these studied properties correlate with the spectral characteristics of the soil. A sharp increase in hygroscopic water content at the 60-80 cm horizon, with a maximum value at the 70 cm depth (Figure 9B: a), clearly correlates with the distribution of SSA parameters throughout the profile. The maximum values, which indicate clayey soil texture, are observed at the same depths (Figure 9B: c). As can be seen from Figure 9B, the carbonate content is relatively low, and increases sharply to 32% at the 40-50 cm depth, and then to 42% in the 80 cm layer. This can be explained by the close proximity of carbonate sandstone deposits, locally referred to as "Kurkar".

Thus, the results we got from the spectroscopic analysis were logical given the environmental conditions. Our findings require further validation by way of chemical laboratory testing.

4. Conclusions

This work demonstrates the possibility of using ground spectral-based approaches for digital quantify and qualify of the some soil properties in situ and in real time, using the nondestructive NIRs procedures. We were able to predict, soil moisture, hygroscopic water, carbonates and SSA at a reasonable level down the profile based on the spectral library containing laboratory and field in-situ collected spectra, which showed that NIRs had potential to accurately predict these constituents in the studied soil. This technology make it possible to visually discern soil characteristics from the spectra, and to then quantify them in the stratigraphy of the soils down the profile, based on the spectral features associated with those constituents. When using the models, input data was exclusively spectral, not based on chemical lab testing. The POC method provides direct measurements at very close spatial intervals, which allows the acquisition of more samples in a given area. In such cases the number of samples required for laboratory analysis may be also substantially reduced. It is obvious, that our study is incomplete. We lack the resources for chemical laboratory analysis, and for statistical correlation between the attributes of the soil surface and the spectral response from the hyperspectral image. We would also prefer to have models based on a more robust sampling of more varied soils. Given the opportunity to expand and complete this study, we would include both air-born and ground based hyperspectroscopy. We hope to gain access to these resources in order to complete our study, refine our method, and launch its application for soil survey.

List of symbols and abbreviations

ACORN, atmospheric correction now; ASD, analytical spectral device; DRS, diffuse reflectance spectroscopy; DNs, digital numbers; ELC, empirical line calibration; ENVI, environment for visualizing images; FAO, Food and Agriculture Organization; GPS, global positioning system; HW, hygroscopic water; IS, imaging spectroscopy; MODTRAN, moderate resolution atmospheric transmission; MNF, minimum noise fraction; NIRs, near infrared analysis; nm, nanometer; POS, penetrating optical sensor; PLSR, partial least square regression; PLS, partial least square; R, correlation coefficient; R^2 , coefficient of determination; RIDs, reflectance inflection differences; RMSE, root mean square error; RMSEP, root mean square error of prediction; SC, soil carbonates; SE, standard error; SEP,

standard error of prediction; SM, soil moisture; SSA, specific soil area; SWIR, short wave infrared; VNIR, visible and near infrared; SNR, signal to noise ratio.

5. References

1. Aly. Z., Bonn. F., and Magagi R., (2004), Modelling the backscattering coefficient of salt-affected soils: application to wadi El- Natrun bottom. In: EARSel Proceedings, 3, Egypt.
2. Analytical Imaging and Geophysics LLC (AIG), (2001), ACORN User's Guide, Stand Alone Version.
3. Banin. A., and Amiel A., (1970), A correlation study of the chemical and physical properties of a group of natural soils of Israel, Geoderma 3, pp 185-198.
4. Baugh. W., and Groeneveld D., (2008), Empirical proof of the empirical line, International Journal of Remote Sensing, 29, pp 665 - 672.
5. Ben-Dor. E., and Banin A., (1990), Near infrared reflectance analysis of carbonates concentration in soils, Applied Spectroscopy, 44, pp 1064–1069.
6. Ben-Dor. E., and Banin A., (1995a), Near infrared analysis as a method to simultaneously evaluate spectral featureless constituents in soil, Soil Science Society of America Journal, 159, pp 259-270.
7. Ben-Dor. E., and Banin A., (1995b), Near infrared analysis (NIRA) as a rapid method to simultaneously evaluate several soil properties, Soil Science Society of America Journal, 59, pp 364–372.
8. Ben-Dor. E., Heller. D., and Chudnovsky A., (2008), A Novel Method of Classifying Soil Profiles in the Field using Optical Means, Soil Science Society of America Journal, 72, pp 1113-1123.
9. Berk. A., Anderson. G.P., Bernstein. L.S., Charya. P.K., Dothe. H., Matthe. M.W., Adler- Golden. S.M., Chetwynd. J.R., Richtsmeier.S.C., Pukall. B., Allred. C.L., Jeong. L.S., and Hoke M.L., (1999), MODTRAN4 radiative transfer model for atmospheric correction. In: Optical Spectroscopic Techniques and Instrumentation for Atmospheric and Space, SPIE Proceeding 3756, pp 348-353.
10. Bricklemyer. R.S., and Brown D.J., (2010), On-the-go VisNIR: potential and limitations for mapping soil clay and organic carbon, Comput. Electron. Agric, 70, pp 209–216.
11. Chang. C.W., Laird. D.A., Mausbach. M.J., and Hurburgh Jr. C.R., (2001), Near-infrared reflectance spectroscopy-principal components regression analysis of soil properties, Soil Science Society of America, 65, pp 480-490.
12. Christy. C. D., (2008), Real-time measurement of soil attributes using on-the-go near infrared reflectance spectroscopy, Comput. Electron. Agric, 61, pp 10-19.
13. Correlation List for the Soils of Israel, 2001,

<http://cals.arizona.edu/OALS/soils/correlation.html>

14. Cozzolino. D., and Moron A., (2003), The potential of Near Infrared Reflectance Spectroscopy to analyse soil chemical and physical characteristics, *Journal of Agricultural Science*, 140, pp 65-71.
15. Dalal. R. C., and Henry R.J., (1986), Simultaneous determination of moisture, organic carbon and total nitrogen by near infrared reflectance spectroscopy, *Soil Science Society of America Journal*, 50, pp 120–123.
16. Dan. J., and Koyumdjisky H., (1979), *The classification of Israel Soils*, The Volcani Center, Bet-Dagan, Israel (Hebrew).
17. Dematte J. A.M., (2002), Characterization and discrimination of soils by their electromagnetic energy, *Agropeg, Brasilia*, 37, pp 1442-1458.
18. Dematte. J. A.M., Campos. R.C, and Alves M.C., (2004), Visible-NIR reflectance: a new approach on soil evaluation, *Geoderma*, 121, pp 95-112.
19. Esbensen K. H., 2002, *Multivariate Data Analysis - in Practice*, 5th edition, Norway, Oslo.
20. Galvao. L. S., Vitorello. I., and Formaggio A.R., (1997), Relationship of Spectral Reflectance and Colour among Surface and Subsurface horizons of tropical soil profiles, *Remote Sensing of Environment*, 61, pp 24-33.
21. Gardner. W.H., (1986), Water content. In: *Methods of soil analysis. Physical and Mineralogical Methods* (ed. A. Klute), American Society of Agronomy and Soil Science Society of America, Madison, pp 493–544.
22. Hunt. G.R., and Salisbury J.W., (1970), Visible and near infrared spectra of minerals and rocks: I. silica minerals, *Modern Geology*, 1, pp 283–300.
23. Kusumo. B. H., Hedley. M. J., Hedley. C. B., and Tuohy M. P., (2011), Measuring carbon dynamics in field soils using soil spectral reflectance: prediction of maize root density, soil organic carbon, and nitrogen content, *Plant Soil*, 338, pp 233–245.
24. Kruse. F.A., Thiry. M and Hauff P.L., (1991), Spectral identification (1.2–2.5 μm) and characterization of Paris basin kaolinite/smectite clays using a field spectrometer In: *Physical Measurements and Signatures in Remote Sensing*, Proc. of the 5th Int. Colloquium, European Space Agency, Paris, pp 181–184.
25. Martens. H., Naes. T., (1987), Multivariate calibration by data compression. In: *Near-infrared technology in the agricultural and food industries*, American Association of Cereal Chemists, Inc., St. Paul, Minnesota, USA.
26. Morra. M.J., Hall.M.H., and Freeborn L.L., (1991), Carbon and nitrogen analysis of soil fractions using near infrared spectroscopy, *Soil Science Society of America Journal*, 55, pp 288- 291.

27. Nanni. M.R., and Dematte J.A.M., (2006), Spectral reflectance methodology in comparison to traditional soil analysis, *Soil Science Society of America Journal*, 70, pp 393–407.
28. Nelson. R.E., (1986), Carbonate and gypsum. In: *Methods of soil analysis. Part 2* (ed. A. Klute), American Society of Agronomy and Soil Science Society of America, Madison, WI, pp 181–197.
29. Rossel. V., Walvoort D.J.J., McBratney A.B., Janik L.J., and Skjemstad J.O., (2006), Visible, near infrared, mid infrared or combined diffuse reflectance spectroscopy for simultaneous assessment of various soil properties, *Geoderma*, 131, pp 59-75.
30. Rossel. V., Cattle R.A., and Ortega Y., (2009), In situ measurements of soil colour, mineral composition and clay content by vis–NIR spectroscopy, *Geoderma*, 150, pp 253- 266.
31. Savitzky. A., and Golay., (1964), Smoothing and differentiation of data by simplified least squares procedures, *Analytical Chemistry*, 36, pp 1627–1639.
32. Simonson R. W., (1995), Airborne dust and its significance to soils, *Geoderma*, 65, pp 1-43.
33. Stevens. A., Wesermael., B.V., Bartholomeus. H., Rossilon. D., Tychon B., and Bendor E., (2008), Laboratory, field and airborne spectroscopy for monitoring organic carbon in agricultural soils, *Geoderma*, 144, pp 395–404.
34. Thomas. G.W., (1986), Exchangeable cation. In: *Methods of soil analysis, Part 2* (ed. A. Klute), American Society of Agronomy and Soil Science Society of America, Madison, WI, pp. 159–165.
35. Tou. J. T., and Gonzalez R. C., (1974), *Pattern Recognition Principles*, Addison-Wesley Publishing Company
36. Waiser. T. H., Brown D.J., and Hallmark C.T., (2007), In situ characterization of soil clay content with visible near-infrared diffuse reflectance spectroscopy, *Soil Science Society of America Journal*, 71, pp 1442-1458.
37. Wu. Chun-Yu., Jacobson. Astrid R.C., Laba. Magdeline Baveye, and Philippe C., (2009), Accounting for surface roughness effects in the near-infrared reflectance sensing of soils, *Geoderma*, 152(1-2), pp 171-180.
38. Yaalon. D. H., and Ganor E., (1973), The influence of dust on soils during the Quaternary, *Soil Science*, 116, pp 146-155.