

# Evaluation of Several Soil Properties Using Convolved TM Spectra

E. BEN-DOR<sup>1</sup>, A. BANIN<sup>2</sup>

1. *Department of Geography, Tel-Aviv University,  
Ramat-Aviv, P.O. Box 39040, Tel-Aviv, Israel,  
69978 bendor@ccsg.tau.ac.il*

2. *Department of Soil and Water Sciences, Faculty of Agriculture, Hebrew University of  
Jerusalem, Rehovot, Israel.*

## Abstract

Laboratory reflectance spectra of ninety-one soil samples from Israel were convolved into the six TM bandpasses allocated within the VIS-NIR-SWIR spectral region (0.4-2.5  $\mu\text{m}$ ). Laboratory convolved TM spectra were used as raw data against which to run the NIRA-VNIRA (Near Infrared Analysis and Visible and Near Infrared Analysis, respectively) procedure using a method called Thematic Mapper Analysis (TMA). Fourteen soil properties and constituents were examined for possible prediction from the TM spectra, but only four were found to be significantly predictable: carbonates ( $\text{CaCO}_3$ ), specific surface area (SSA), total silica ( $\text{SiO}_2$ ) and loss-on-ignition residual (LOI). Prediction performance of the method is still low relative to the results obtained using a similar population and an analysis routine for highest spectral resolution data, however the extremely difficult conditions used (low spectral resolution and complex soil matrix), the prediction performance is likely to be good and is very promising for the remote sensing applications of soils. Further study with real TM data and field measurements is strongly recommended.

## 1. Introduction

Near Infrared Analysis (NIRA in the 1.0-2.5  $\mu\text{m}$  spectral region) and Visible-Near Infrared Analysis (VNIRA in the 0.4-1.0  $\mu\text{m}$  spectral region) methodologies are similar routines that have been successfully used to predict several soil properties from their reflectance spectra (BEN-DOR and BANIN, 1994a,b). Basically, NIRA is a method

that was developed to predict the concentration of a given constituent that consists of significant spectral features in the short wave infrared (SWIR) spectral region. Recently, BEN-DOR *et al.* (1994a) successfully applied the NIRA concept into featureless soil constituents in the visible and near infrared regions and concluded that low spectral resolution is not necessarily a limitation for quantitative analysis of soils.

The TM data have been widely studied for various applications by using various analytical techniques such as band rationing, color composite technique, analysis of the TM spectrum (unmixing) are clustering analysis, discriminate analysis, and principle component analysis (PCA). Soil is a complex system of minerals, organic matter and water, and hence may prove to be complicated in their analysis. Based on a modified stepwise principal component analysis, CSILLAG *et al.* (1993), showed that salinity of soils can be detected using six broad bands across the VIS-NIR-SWIR region as derived from high resolution spectra. They pointed out that their identified bands may yield higher overall accuracy than that currently available from Landsat MSS, TM, and SPOT XS in terms of spectral recognition of salinity status.

In another study, PRICE (1990) concluded that four broad-band spectral measurements across the VIS-NIR-SWIR region, as derived from high spectral resolution of more than 500 soils, are sufficient to describe their spectra.

Based on the idea that the six broad spectral bands of the TM spectrum does hold chemical information in the VIS-NIR-SWIR regions and based on the fact that the NIRA-VNIRA methods successfully run on low spectral resolution spectra, we applied and report here a study that examines the synergy between TM spectra and NIRA approach.

## **2. Materials and methods**

### **Soil sampling**

Ninety-one soil samples that represent twelve soil groups in Israel were selected to cover the arid and semiarid climatic zone of Israel (BEN-DOR and BANIN, 1994b). The samples were collected mostly from the A0 horizon of the soils (upper 5 cm) within an area of about 1 m<sup>2</sup>. The soils were air dried and gently crushed to pass through a < 2 mm sieve. Subsamples were further grounded (quantitatively) by agate mortar to pass through a 0.355 mm sieve.

### **Chemical and mechanical analyses**

The following soil properties and constituents were determined by applying laboratory techniques that are mostly summarized in the "Method of Soil Analysis" text

book (MILLER and KEENY, 1986), these being: Clay content (CLAY), Specific surface area (SSA), Cation exchange capacity (CEC), Hygroscopic moisture (HIGF), Exchangeable sodium percentages (CNaP), Calcium carbonate content ( $\text{CaCO}_3$ ), and Organic matter content (OM). The total elemental analyses (iron- $\text{Fe}_2\text{O}_3$ , alumina- $\text{Al}_2\text{O}_3$ , silica- $\text{SiO}_2$ , loss-on-ignition residual-LOI, and potassium- $\text{K}_2\text{O}$ ) were carried out using the X-ray fluorescence method at XRAL Laboratories (Canada) and the free iron oxides (Fed) were determined by using the Dithionite Citrate Bicarbonate (DCB) method provided by MEHRA and JACKSON (1960). Soil aggregate size distribution was accomplished through differential sieving of the < 2 mm dry soils. The sieving procedure consisted of shaking 400 grams of soil for five minutes through six different sieves as follows: 2-1.4 mm (F1), 1.4-1.0 mm (F2), 1-0.5 mm (F3), 0.5-0.25 mm (F4), 0.25-0.1 mm (F5) and < 0.1 mm (F6). Soil materials remaining on each of the sieves after the shaking period were accurately weighed and reported as percentages of the initial 400 grams of material. The average aggregate size (AVGR) was calculated as a geometrical mean of the six aggregate size fractions.

$$AVGR = \sum_{i=1}^6 W_{F_i} \cdot \frac{d_{F_i}}{400}$$

where  $W_{F_i}$  is the weight (in grams) of fraction  $F_i$ , left on the corresponding sieve,  $d_{F_i}$  is the average size of the relevant  $F_i$  fraction and 400 refers to the initial weight of the soil sample examined.

## **Spectral measurements and compression**

Spectral measurements: Soil reflectance spectra were recorded separately by two spectrophotometers for the VIS-NIR (0.4-1.1  $\mu\text{m}$ ) and SWIR (1-2.5  $\mu\text{m}$ ) regions as follows: For the SWIR region, we used an Alpha Centauri MATTSON FTIR spectrophotometer optimized to the SWIR (1-2.5  $\mu\text{m}$ ) region (spectral resolution of 1.9  $\text{cm}^{-1}$ , in terms of wavenumber, providing 3,113 non equal spectral bands) and a Prying Mantis bidirectional Harrick diffuse reflectance attachment (DRA two dimensional model). For the VIS-NIR region, we used a LICOR spectrometer optimized to the VIS-NIR region (0.4-1.1  $\mu\text{m}$ ; spectral resolution of 1 nm, in terms of wave number providing 700 equal spectral bands) and an integrating sphere attachment coated with  $\text{BaSO}_4$ . In both of the above spectral regions, a standard sample preparation routine was applied to the < 0.355 mm soil powders and the soil reflectance spectrum was reported relative to a  $\text{BaSO}_4$  spectrum.

Spectrum compression into TM bands: In both VIS-NIR and SWIR regions the spectral and wavelength values of all original bands that were allocated within the TM spectral bands were averaged. Table 1 presents the TM bands, together with their spectral regions. Table 1 also shows the average wavelength of each TM band and the number of original spectral bands required for the calculation of the convolved TM values (both for wavelength and spectral readings).

**Table 1.** The TM bands and their spectral ranges together with the convolved wavelength and number of spectral points taken for the convolution process.

TM band	Spectral range (mm)	Convolved wavelength (mm)	Spectral points in convolved bandpass
TM1	0.40-0.52	0.46	120
TM2	0.52-0.60	0.56	80
TM3	0.62-0.69	0.66	70
TM4	0.76-0.94	0.83	140
TM5	1.55-1.75	1.65	383
TM6	10.4-12.56	N.D.*	N.D.*
TM7	2.08-2.35	2.22	285

\* Not determined.

## Spectral Analysis

The NIRA-VNIRA methodology that is used to analyze the convolved TM spectra is termed Thematic Mapper Analysis (TMA). The TMA (and NIRA-VNIRA) procedure requires two stages: 1) the calibration stage, where the prediction equation is developed, and 2) the validation stage, where the previous stage is validated (DAVIES and GRANT, 1987). Since the suggested algorithm is basically an empirical method, the validation stage is extremely critical. The complete TMA procedure absolutely requires both the calibration and the validation stages to predict unknown samples.

### Calibration stage

This procedure utilized a subgroup (22-50 samples) that was selected directly from the ninety-one soil samples. A simple linear regression procedure between the concentration of a given constituent and the spectral response (reflectance [R], absorption [ $A=\log(1/R)$ ] or their derivatives [first-R', A', and second-A'']) of every band was run. A Multiple Regression Analysis (MRA) was run between the chemical values and all six TM bands and their corresponding reflectance values. This procedure was used to examine each of the spectral parameters (R, A, or their derivatives) and each MRA stage. The result, a multi-term equation, was then used to predict the concentration of "unknown" validated samples in stage 2.

### Validation stage

Unknown subgroups (37-56 samples) that were not used in the calibration process were used to validate the calibration equation produced in stage 1. For that purpose, the spectra of all the validation samples were mathematically manipulated exactly as were the spectra that provided the prediction equation. Then the concentration of each constituent was calculated using the corresponding prediction equation obtained in stage 1. The calculated results (predicted) were compared with the chemical results (measured). Every prediction equation of the calibration stage for each of the MRA

steps was examined against the validation subgroup. The prediction equation that yielded the highest validation performance was declared the preferred equation, and used further in this study.

### Statistical Analyses

The MRA procedure selects a best multiple correlation equation between a constituent concentration  $C_p$  in a given sample and the selected spectral parameters as follows:

$$C_p = b_0 + b_1 L_1 + b_2 L_2 + \dots + b_n L_n \quad (1)$$

where  $b_0$  is an intercept,  $b_1, b_2, \dots, b_n$  are weighting factors for the spectra readings in various selected wavelengths 1 to  $n$ .  $L_1, L_2, \dots, L_n$  are the values of the spectral parameters at wavelengths 1 to  $n$  and could be either reflectance data (R), absorption data (A) or their derivatives (first R', A' or second A"). Predicted values of the constituents' concentrations were calculated from equation 1 and the standard error of calibration (SEC) was then calculated according to DAVIES and GRANT (1987) as follows:

$$SEC = \sqrt{\frac{\sum (C_m - C_p)^2}{N_c - n - 1}} \quad (2)$$

where  $C_m$  is the value measured by the chemical analysis,  $C_p$  is the predicted value on the basis of the spectral analysis,  $N_c$  is the number of the samples in the set and  $n$  is the number of terms in the prediction equation.

The calibration equation (2) was used to predict the constituent concentration of another set of soil samples not used in the calibration stage. The standard error of performance (SEP) was then calculated as follows:

$$SEP = \sqrt{\frac{\sum (C_m - C_p)^2}{N_v - 1}} \quad (3)$$

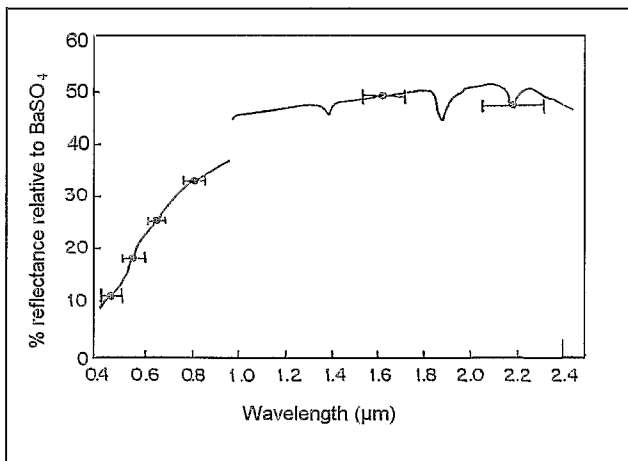
where  $N_v$  is the total number of tested samples in this stage.

In addition to the above parameters, we applied a bias test that was adopted from MILLER and MILLER (1988). It examines the regression line between the results of the reference and the alternative methods (in our case the chemical and the TM-validation results respectively) and uses three null hypotheses in order to reject or accept the regression line ( $C_p = a.C_m + b$ ) as a 1:1 line. The assumptions of the null hypotheses are:

- 1) The slope of the regression line (a) is unity,
- 2) The intercept of the regression line (b) is zero and,
- 3) The regression coefficient ( $r^2$ ) is unity.

### 3. Results and discussion

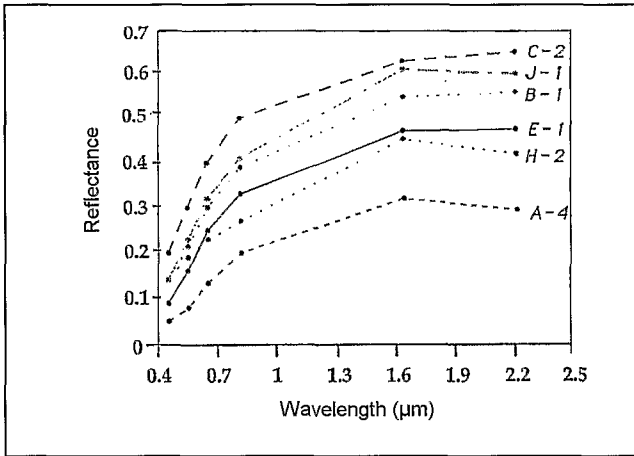
In figure 1 the original reflectance spectrum of a representative soil (B-7) together with the six TM band passes in the VIS-NIR-SWIR regions, is presented. Figure 2 indicates that convolving the original spectra into the six TM band passes significantly affects the spectral features of the continuous spectrum. In order to roughly examine the effect of compressing the original spectrum into the TM spectrum, we compared the soil chemistry with some of their convolved TM spectra. In figure 2, six convolved TM spectra of six representative soil samples are presented. Table 3 presents the chemistry of these selected soils as determined by chemical methods and their classification according to the United States Department of Agriculture (USDA). In general, the TM spectra of the soils are quite similar. However, some differences can be observed, mainly in the apparent reflectance values. Apparent reflectance actually relates to the soil brightness (or soil "albedo") and correlates with the  $\text{CaCO}_3$  content while showing a correlation with the Fed and OM amounts. A high content of  $\text{CaCO}_3$  is attributed to a light soil color (and hence to higher VIS reflectance, BAUER *et al.*, 1979), a high Fed content is attributed to red soil color (and hence to a moderate to low VIS reflectance, SCHWERTMANN, 1988) and a high OM content is attributed to dark soil color (and hence to the lowest VIS reflectance MCKEAGUE *et al.*, 1971).



**Figure 1.** Reflectance spectrum of representative soil sample B-7 in the VIS-NIR-SWIR spectral region (0.4-2.5 $\mu\text{m}$ ) and the positions of six TM band # passes allocated in this region.

Thus, sample C-2, which contains a relatively high amount of  $\text{CaCO}_3$  (40.3%) and relatively low amounts of Fed (1,967 ppm) and OM (1.02%) presents high reflectance levels throughout all spectral regions (high albedo). Sample A-4, which contains relatively high amounts of Fed (14,794 ppm) and OM (5.65%) and has a relatively low  $\text{CaCO}_3$  content (8.45%), presents low reflectance levels throughout all spectral regions (low albedo). Also note that soils with a relatively high Fed content (A-4, H-2, and E-1) have a spectral feature around 0.56  $\mu\text{m}$ , which can be assigned to ferrous ion (HUNT *et al.* 1971). A relatively high content of clay (A-4, H-2, and J-1) shows a

negative slope of the TM curve going from band TM5 to band TM7 because of the relatively high absorption of OH in clay minerals at around 2.2  $\mu\text{m}$  (band TM7). It can be concluded that even though the convolved TM spectra contain only six spectral bands, and much of the spectral information is apparently reduced by the spectral compression, important information concerning the chemistry of the soils can still be roughly extracted from the convolved TM spectra.



**Figure 2.** Convolved TM reflectance spectra of six representative soils. Each of the soils corresponds to a different soil group as classified according to the USDA classification method (see Table 2).

**Table 2.** Chemical values of six representative soil samples and their classifications according to the USDA.

Soil Sample	USDA Classification	CaCO <sub>3</sub> (%)	Clay (%)	Fed (ppm)	OM (%)
E-1	Rhodoxeralf	1.83	13.9	4,302	1.27
C-2	Xerorthent	40.3	19.1	1,967	1.02
B-1	Haploxeroll	41.99	39.3	5,253	4.91
A-4	Xerochrept	8.45	46.1	17,794	5.65
H-2	Xerent	18.5	61.2	3,876	1.85
J-1	Fluvent	38.9	50.6	6,777	1.14

Based on the above, we further studied the relationship between the TM spectra and the soil chemistry by using the TMA approach. For that purpose we used all manipulated spectra as discussed in the *Material and method* section. To illustrate the influence of the mathematical manipulations on a given spectrum, in figure 3 we present the original convolved TM spectrum of sample B-7 together with its absorbance, and first and second derivatives of the absorbance TM convolved spectrum. It is apparent that the conversion of reflectance data ( $R$ ) into absorbance values ( $A = \log [1/R]$ ) does not affect the original TM spectral features. Also notice that the first derivation technique yields a curve that looks quite similar to the original TM reflectance curve, except for slight spectral enhancement around 0.4-0.7 mm. The second derivative better "enhanced" the VIS region and a significant peak can be detected around 0.57 mm.

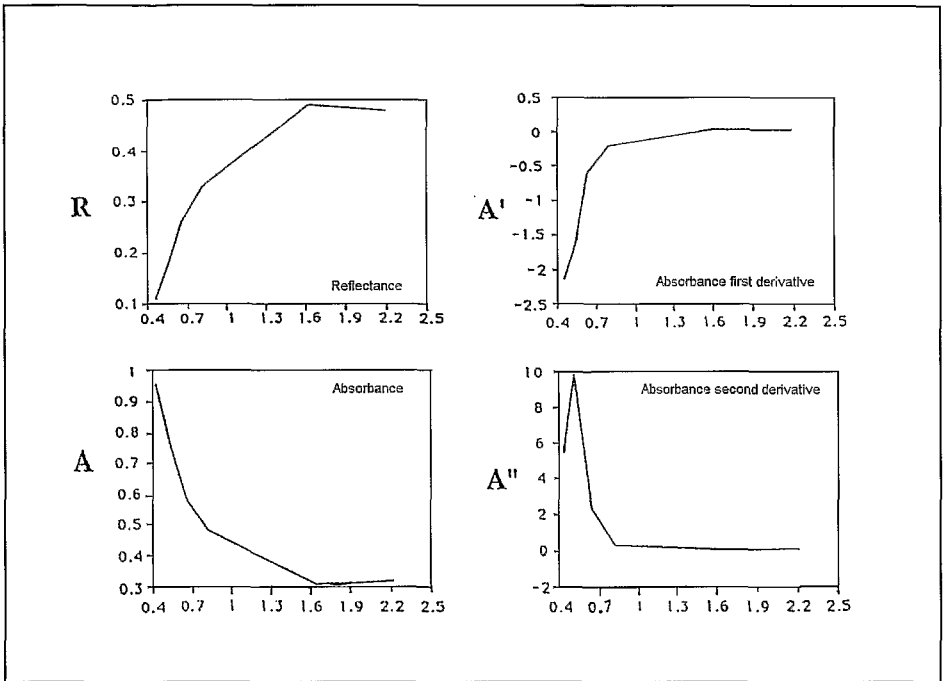
**Table 3.** The optimal results for each manipulation stage (R, A, R', A', A''). The optimal information includes:  $r^2$  and SEP of the validation stage,  $R^2$  and SEC of the calibration stage and the first wavelength in the prediction equation. Values in bold represent the prediction stage selected.

Group	Property	Math $r^2$ - SEP $R^2$ - SEC $\lambda_1$	Group	Property	Math $r^2$ - SEP $R^2$ - SEC $\lambda_1$	Group	Property	Math $r^2$ - SEP $R^2$ - SEC $\lambda_1$
I	CaCO <sub>3</sub> (%)	A <b>0.69 - 11.40</b> 0.79 - 11.07 0.46 $\mu$ m	III	HIGF (%)	A 0.40 - 1.98 0.54 - 2.01 0.83 $\mu$ m	IV	Fed (ppm)	A 0.41 - 3341 0.50 - 2930 0.66 $\mu$ m
II	OM (%)	A 0.39 - 2.03 0.36 - 1.38 0.66 $\mu$ m	III	Al <sub>2</sub> O <sub>3</sub> (%)	A 0.26 - 2.51 0.35 - 2.54 0.83 $\mu$ m	IV	AVGR(mm)	A' 0.10 - 0.18 0.12 - 0.19 1.65 $\mu$ m
III	SSA (%)	A <b>0.46 - 63.8</b> 0.60 - 60.8 0.83 $\mu$ m	III	Fe <sub>2</sub> O <sub>3</sub> (%)	R 0.27 - 1.39 0.37 - 1.26 0.83 $\mu$ m	IV	Fi (%)	R' 0.29 - 5.61 0.21 - 6.69 0.56 $\mu$ m
III	CEC (%)	A 0.41 - 10.7 0.54 - 9.97 0.83 $\mu$ m	III	SiO <sub>2</sub> (%)	A <b>0.67 - 12.60</b> 0.68 - 13.34 1.65 $\mu$ m	IV	CNap (%)	A 0.17 - 0.37 0.10 - 0.36 0.46 $\mu$ m
III	Clay (%)	R 0.28 - 12.50 0.39 - 13.19 0.66 $\mu$ m	III	LOI (%)	A <b>0.71 - 5.71</b> 0.80 - 4.67 1.65 $\mu$ m	IV	K <sub>2</sub> O (%)	A 0.17 - 0.37 0.10 - 0.36 0.46 $\mu$ m

Math: spectral mathematic manipulation(R-Reflectance;A-Absorbance;R'&A'-First derivatives; A''-Second derivative);  $r^2$ : Single coefficient of correlation between validation data; SEP: Standard error of prediction;  $R^2$ : Multiple coefficient of correlation between calibration data; SEC: Standard error of calibration;  $\lambda_1$ : First wavelength in the calibration equation.

NIRA-VNIRA (and TMA) techniques require the selection of a representative calibration set, which is chemically matched with its validation set and with the population of a large number of samples (MURRAY, 1988). Since we identified four different groups of properties, four independent testing groups were used for the TMA examination. Basically the NIRA approach (and hence the TMA as well) is an empirical method that allows (actually requires) many combinations of samples and data manipulations to obtain optimal prediction performance (STARK, 1988). The criteria of low SEP and high  $r^2$  of the validation set were selected to indicate the optimal data manipulation. The results of this initial analysis are presented in table 5 where the data manipulation (A, R, R', A' or A'') that yielded the best performance along with their statistical parameters ( $r^2$ , SEP,  $R^2$ , SEC), and with the first wavelength of the prediction equation ( $\lambda_1$ ), are presented.





**Figure 3.** The effect of converting the convolved TM reflectance spectrum of a representative soil sample (B-7) into absorbance (A) and its manipulation into first (A') and second (A'') derivatives.

From table 3 it can be seen that most of the predictions (and particularly those with  $r^2 > 0.45$ ) require transformation into A with no derivation. Only four constituents could be reasonably predicted using the convolved TM spectra:  $\text{CaCO}_3$ , SSA,  $\text{SiO}_2$ , and LOI.

NORRIS and WILLIAMS (1984) concluded that the derivation technique eliminates the baseline differentiation caused by particle size distribution (termed "particle size effect"). Based on the fact that significant TMA predictions do not require derivation manipulation, it may be concluded that TMA predictions strongly depend on the apparent reflectance (albedo) rather than on specific absorption. To examine this issue, we further studied the prediction equations of the four significant properties. Table 4 presents the optimal prediction equations along with their suggested wavelength assignments.  $\text{CaCO}_3$  is predicted by three bands in the VIS region: 0.46, 0.56 and 0.66 mm (bands TM1, TM2, and TM3, respectively). Since  $\text{CaCO}_3$  does not have any spectral features in the VIS region, it is predicted by the soil brightness (albedo). BEN-DOR and BANIN, (1994a) concluded that even the highest spectral resolution data in the VIS region required that  $\text{CaCO}_3$  be predicted via soil albedo. The first wavelength chosen by the TMA procedure to be part of the prediction equation (which is considered to be the most important part in the equation) was 0.46 mm (band TM1)

which is quite similar to the first wavelength that BEN-DOR and BANIN (1994b) found for the prediction of  $\text{CaCO}_3$  from soils (0.401 mm) using higher resolution spectra.

**Table 4.** The best calibration equations for predicting four soil constituents and this suggested wavelength assignments which were entered into the calibration equation. The selection of each equation was based on table 5.

Property	Mathematics (spectral bands)	Constant ( $b_0$ )	Weighting coefficient ( $b_1$ )	Wavelength h ( $\mu\text{m}$ )	TM band	Suggested assignment
$\text{CaCO}_3$	A (6)	115.7	-325.1	0.66	TM3	Soil brightness
			657.2	0.56	TM2	"
			-407.6	<b>0.46</b>	TM1	"
SSA	A (6)	96.7	4711.3	2.22	TM7	$\nu + \lambda$ (OH-Al)
			-4696.7	1.65	TM5	$\nu + \lambda$ (OH-Al)
			799	0.83	TM4	$3\nu$ (OH-Al)
			-216.2	0.46	TM1	-
$\text{SiO}_2$	A (6)	10.06	-495.9	2.22	TM7	$\nu + \lambda$ (OH-Al)
			794.9	1.65	TM5	-
			-216.9	0.83	TM4	$3\nu$ (OH-Al)
			46.7	0.46	TM1	$\text{CaCO}_3$ assignment
LOI	A (6)	42.21	201.5	2.22	TM7	$\nu + \lambda$ (OH-Al)
			-314.3	1.65	TM5	-
			12.2	0.83	TM4	$3\nu$ (OH-Al)
			115.3	0.56	TM2	$\text{CaCO}_3$ assignment
			-80.7	0.46	TM1	$\text{CaCO}_3$ assignment

$\nu$  = stretching mode,  $\lambda$  = bending mode.

Table 5 presents the linear correlation coefficient matrices of several important properties. It can be clearly seen that a high correlation occurs between  $\text{CaCO}_3$ - $\text{SiO}_2$  and  $\text{CaCO}_3$ -LOI ( $r = -0.899$  and  $0.913$ , respectively) and between SSA-Clay and SSA- $\text{Al}_2\text{O}_3$  ( $r = 0.824$  and  $0.830$  respectively). As BEN-DOR and BANIN (1994a) pointed out, intercorrelation is the major mechanism that enables featureless soil properties to be predicted by the VNIRA-NIRA methodologies.  $\text{SiO}_2$ , LOI and SSA, belong to the same "chemical" group (Group III). SSA is a property that relies mainly on the smectite mineral content, which is considered to be the major clay mineral in Israeli soils (BANIN and AMIEL, 1970). Thus, the SSA assignments are attributed to the combination mode of OH (at band TM7), the third overtone of OH (at band TM4), and probably to Fe (mostly in the structural formation as presented by a high correlation with  $\text{Fe}_2\text{O}_3$  ( $r = 0.878$ ) and partially by the free Fe as presented by moderate correlation with Fed ( $r = 0.617$ )). LOI is a property that represents the loss of weight during ignition. This property is a combination of organic matter removal, dehydroxylation of the lattice OH group and decarboxylation of  $\text{CO}_3$  groups (MACKENZIE 1957). From table 5 it can be seen that the LOI highly correlates with  $\text{CaCO}_3$  ( $r = 0.913$ ) and has a low correlation with OM ( $r = 0.401$ ) and SSA ( $r = 0.279$ ). Therefore we assume that the decarboxylation reaction is a major contributor to the LOI values and hence mostly

to CaCO<sub>3</sub> minerals (bands TM2 and TM3) and to OH combination mode in clay minerals (band TM7). The SiO<sub>2</sub> is inversely correlated with the LOI and CaCO<sub>3</sub> (r = -0.899 and -0.983, respectively) and therefore was assigned to the LOI and CaCO<sub>3</sub> wavelengths.

**Table 5.** Coefficient of correlation (r) between all of the soil properties studied. The correlation was determined using only the chemical values.

	CaCO <sub>3</sub>	OM	SSA	Clay	Al <sub>2</sub> O <sub>3</sub>	Fe <sub>2</sub> O <sub>3</sub>	SiO <sub>2</sub>	LOI	Fed
CaCO <sub>3</sub>	1	0.059	-0.037	0.1616	-0.366	-0.284	-	0.913	-0.381
OM		1	0.511	0.413	0.475	0.501	-0.341	0.401	0.462
SSA			1	0.824**	0.830**	0.878**	-0.326	0.279	0.617*
Clay				1	0.645	0.686*	-0.415	0.393	0.529*
Al <sub>2</sub> O <sub>3</sub>					1	0.979**	-0.035	-0.049	0.815*
Fe <sub>2</sub> O <sub>3</sub>						1	-0.126	0.045	0.808*
SiO <sub>2</sub>							1	-	0.046
LOI								1	-0.115
Fed									1

\* Significant at 0.95 level; \*\* Significant at 0.99 level.

Figure 4 presents the "Predicted" vs. "Measured" values of the calibration (A) and validation (B) sets. The values for all properties and for both sets appear to fall in the vicinity of the 1:1 line. However, in most of the properties (especially in the validation stage) some bias can be observed. Table 6 presents the regression line ( $C_p = aC_m + b$ ) parameters (a, b and r<sup>2</sup>) of the validation stage along with their statistical significance based on MILLER and MILLER test (1988). Only SSA does not significantly match the 1:1 line, and therefore holds bias. The other properties (CaCO<sub>3</sub>, SiO<sub>2</sub>, and LOI) do not significantly differ from the ideal 1:1 line (for both a and b parameters), and therefore hold no bias.

**Table 6.** The regression line parameters (r<sup>2</sup>-coefficient of correlation, a-slope and b-the intercept) of seven soil properties in the validation stage. Also shown are the parameters significance (at 0.95), that the r<sup>2</sup> is not different from unity, a is not differ from 1 and b is not different from 0 (see text).

	SEP	r <sup>2</sup>	a	b
CaCO <sub>3</sub>	11.4	0.69*	0.84*	6.34*
SSA	63.8	0.46	0.47	77.21
SiO <sub>2</sub>	12.6	0.67*	0.71*	11.15*
LOI	5.71	0.71*	0.75*	6.12*

\* Significant at 0.95 level.

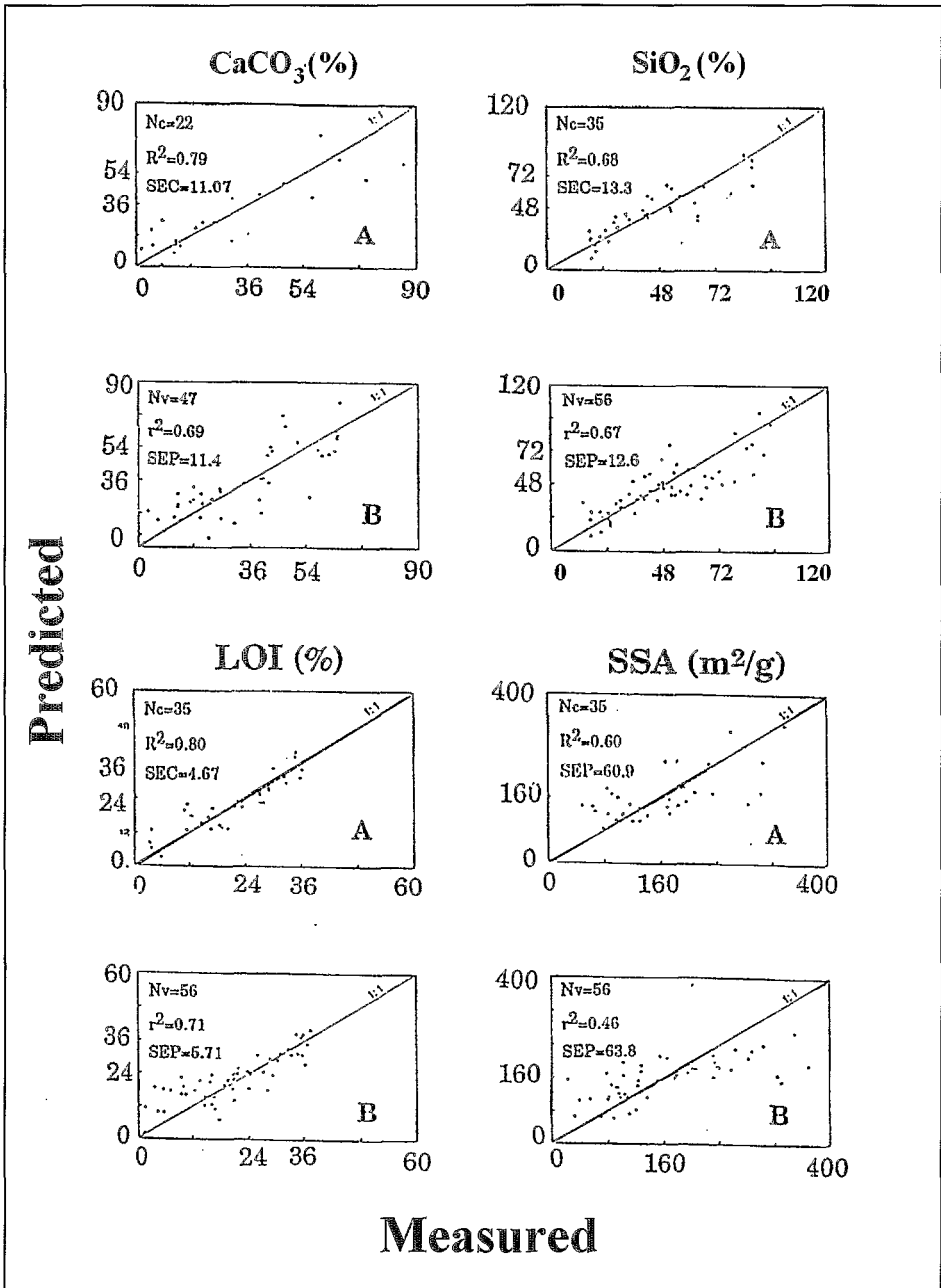


Figure 4. Plots of the predicted ( $C_p$ ) vs. measured ( $C_m$ ) values at the calibration (A) and validation (B) stages for the optimal TMA prediction of the significant soil properties.

The SEP value is a major criterion used to judge the prediction performance of the NIRA methodology (DAVIES and GRANT, 1987). Relatively low SEP values, combined with SEP and SEC values that are relatively close, are major conditions for optimal prediction (NORRIS and WILLIAMS, 1984). From table 3 it can be seen that the SEP values in all of the selected stages are similar to the SEC values. Although the SEP values of the selected stages were relatively low, major consideration should be given to the coefficient of prediction variance ( $CPV=SEP/[Max-Min]$ ) and to the chemical performance.

Table 7 presents the SEC and SEP values of the selected optimal stages (i.e., stage with the highest performance), the analytical error (AE) of the chemical analysis, the chemical range of the validation set [Max-Min], the coefficient of prediction variance ( $CPV = SEP/(Max-Min)$ ) and the SEP/AE ratio. It can be seen that the CPV values varied between 15% and 18%. A relatively high prediction performance was obtained for the SSA (15%) and a relatively low prediction performance was obtained for the SiO<sub>2</sub> (18%). A comparison of the SEP and the analytical error (AE) indicates that the TMA prediction performance still lags behind the chemical performance.

**Table 7.** Statistical parameters of the calibration, validation and the chemical stages.

Property	SEC <sup>1</sup>	SEP <sup>2</sup>	AE <sup>3</sup>	Max-Min <sup>4</sup>	CPV <sup>5</sup>	SEP/AE
CaCO <sub>3</sub>	11.07	11.40	1.3	65.3	0.17	8.77
SSA	60.8	63.8	4.0	414.1	0.15	15.95
SiO <sub>2</sub>	13.34	12.60	1*	70.3	0.18	12.60
LOI	4.67	5.71	1*	36.19	0.16	5.71

1: SEC - Standard error of calibration; 2: SEP - Standard error of prediction; 3: AE - Analytical error; 4: Max-Min - Validation chemical range; 5: CPV - Coefficient of prediction variation,  $SEP/(Max-Min)$ ; \*: Estimated values.

In order to compare the TMA analysis results obtained here to the optimal NIRA-VNIRA results obtained elsewhere (for the same soil populations and for the entire spectral region), we further studied the SEP values. Table 8 presents the optimal SEP values obtained for the four significant properties (CaCO<sub>3</sub>, SSA, SiO<sub>2</sub>, LOI) using TMA, VNIRA (BEN-DOR and BANIN, 1994b) and NIRA (BEN-DOR and BANIN, 1994a) techniques. It can be seen that both the VNIRA and the NIRA routines gave a better performance than the TMA procedure. However, for the above properties, the TMA method gave a prediction performance that was not much different than those of the VNIRA and NIRA routines. Considering the relatively broad band the convolved TM spectra consists of, and its undersampling, it can be concluded that the TMA approach may be very promising for remote sensing applications of soils. However, further study is needed to examine the performance of the TMA strategy in the field using real TM data.

**Table 8.** Comparison between prediction performances obtained by the TMA, VNIRA and NIRA approaches for the same soil samples.

Property	Group <sup>a</sup>	SEP in TMA Prediction	SEP in VNIRA or NIRA Prediction <sup>**</sup>
CaCO <sub>3</sub>	I	11.4	11.3 (VNIRA)
SSA	III	63.8	50.5 (NIRA)
SiO <sub>2</sub>	III	12.6	11.9 (NIRA)
LOI	III	5.71	4.03 (NIRA)

\* According to table 2.; \*\* According to BEN-DOR *et al.*, 1991 and BEN-DOR and BANIN, 1993.

#### 4. Summary and conclusions

Convolved TM spectra of soils contained important information regarding several soil properties and constituents. There is a rough but positive correlation between TM spectra and the soil chemistry based on soil brightness or albedo. The derivation technique enhances some of the VIS region in various samples, while in other samples it does not. The TMA methodology was found to be a sufficient vehicle to estimate CaCO<sub>3</sub>, SSA, SiO<sub>2</sub>, and LOI in soils. It is assumed that an intercorrelation between CaCO<sub>3</sub> and other constituents was the major mechanism that enables the prediction of these properties. Although the TMA results show a relatively low prediction performance compared to the analytical, VNIRA, and NIRA results, the TMA performance is likely to be useful for remote-sensing applications of soils.

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