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SATELLITE DIGITAL DATA ANALYSIS FOR SOIL PROPERTIES PREDICTION AND MAPPING UNITS OF BARE DESERT SOIL, EGYPT

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ABSTRACT

This study was carried out to predict some surface soil properties and mapping units of some bare desert soil throught the analysis of satellite digital data. Spatial variability of some surface soil properties was studied using coefficients of variation and multivariate analysis were used to predict all the studied surface soil properties. Geographical information system processes were used to map the original and predicted soil attributes variability and mapping units.

The image processing showed that the area can be classified to bare soil (86.4 ٪(and vegetated area (13.6 ٪(. The vegetated area has three levels of natural vegetation density: high, moderate and low. The supervised and unsupervised classifications using spectral signature techniques showed that the bare soil area can be subdivided to five classes with the same shapes and different attitudes.

The statistical analysis have been done for seven different combination of data sets depending on the number of the surface samples of augers, profiles and sectors with presence and absent of natural vegetation. The descriptive statistical analysis showed that the highly variable soil properties (CV > 60 ٪(on the area are $CaCO_3$ ٪ and EC and the rest soil properties has medium effect (CV between 10 and 60 ٪(for 80 and 68 data sets. While, for 20 and 17 data sets, the very high soil variability caused by $CaCO_3$ ٪, infiltration rate, EC, gravel ٪ and hydraulic conductively. In the same time, the grain size distribution has medium effect. All color components has medium effect even under dry or wet conditions with CV values between 10 and 60%. The digital numbers for all data sets has very low effect (CV<10 ٪(on the soil variability except for bands 2, 3, and 7 for 80 surface samples and for all bands for 20 sample size, which has CV between 10 and 20٪

The multivariate regression analysis have been successfully applied to all soil properties using extracted image digital numbers. The R values for $CaCO_3$ ٪ and EC ranged between 0.705 to 0.867 and 0.748 to 0.781, respectively. For sample size 80 and 68, the R values for all predicted available nutrients, cation exchange capacity and organic matter were more than 0.953. The predicted color components under dry and wet conditions had R values more than 0.910 for 20 sectors, and 20 and 17 profiles data sets as well as sand, silt and clay, while for gravel % was 0.803. Infiltration rate has the least R values (0.757) and hydraulic conductivity had more than 0.904 value.

The Spatial variability of the original and predicted values of $CaCO_3$ ٪ and EC from image digital numbers have been mapped for comparison. The average accuracy for $CaCO_3$ ٪ and EC were 91.45٪ and 88.70 ٪, respectively, while their mapping units has 87.88 % average accuracy. This results showed the high potentials of using digital numbers of satellite image for predicting soil properties and mapping units.

Keywords: Satellite digital number, Bare soil, Soil properties, Spatial variability, Prediction, Mapping units, Accuracy.

INTRODUCTION

A soil survey is a field investigation of soils in a given area, to determine the spatial extent of similar map units within a landscape. Field work and soil maps are usually supported by tabular information on soil properties, limitation and use. These are derived from other sources and are based on point measurements, or estimates for representative, or model profiles of that soil (Rogowski and Wolf, 1994 and Rogowski, 1995).

Satellite sensors capable of acquiring frequent coverage would seem to have the potential for producing and updating resource maps. So, inventory and monitoring are very important processes for soil reclamation and agriculture production. Increasing the spatial resolution of such data would increase the using potential and decreasing the back ground effect, especially for large area of bare soil. The representative sampling area range between 5 to 15 % from the total area. Soil reflectance properties result from cumulative effects of the heterogeneous combination of all soil chemical and physical properties. The main factors affecting the spectral soil reflectance are mineralogy and chemical constituents, organic matter, particle size, surface roughness, and water content. Cluster techniques used for supervised (Huang, 2002) and unsupervised (Viovy, 2000) classification is one of the most often used methods for extracting information from remotely sensed data. Clustering can also be used to determine the natural spectral grouping present in a data set (Huang, 2002). There are two main techniques of clustering methods: Iterative Self-Organizing Data Analysis (ISODATA) and hierarchical approaches (Viovy, 2000). The acceptable accuracy of the classification process with a time consuming process was described in ERDAS, 1997. It does not matter where the initial cluster centers are located, as long as, enough numbers of iterations (or processing time) is allowed.

Sohn and McCoy, 1997, showed that the linear spectral un-mixing model can provide moderate estimates of vegetation fractions in arid rangeland, where vegetation is sparse, with TM data over an area in long Valley, Nevada, USA. Also, from curve shape, they were able to distinguish between bare soil and vegetated land cover types and also differentiate between different soil color conditions. Han,1997, found that soil spectral curves, associated with different moisture content, remained similar in shape. However, the separation of the same soil type, dry (light) and wet (dark) curves increased as wavelength increased. Bahnassy *et al*. 1999, found that the Lagoon soils spectral curve characteristic had a concave shape in visible wavelengths due to the effect of lime-stone deposits dominated in the soil surface layer. Curran and Atinson, 1999, described the powerful relation between geostatistics and remote sensing. They stated that geostatistics can be used to describe the spatial variation in ground and remotely sensed data. They used it to design optimum sampling scheme for both data sets and to increase their accuracy. Ben-Dor *et al*. 2002, used hyper-spectral data to produce prediction equation model for soil organic matter, field moisture and salinity and finally to produce their quantitative maps.

The objectives of the current research is to use the high potential ability of satellite image of bare soil to predict different soil properties and to evaluate the extent of variability associated with field measured and estimated soil data for mapping some soil properties and soil mapping units and determine maps accuracy.

MATERIALS AND METHODS

Site description

Location: The representative studied sampling area (2000 feddans) locates on the western side of Cairo-Alexandria desert road between km 84 to 86 in the vicinity of the Sadat City. The area extends 5 km's to the west of the desert road (Fig. 1). It has undulating topography and the highest elevation, 69 m above sea level, is located in the south western portion of the area. So, the land slopes directs to North and East reaching the lowest elevation of 57 m. It is generally barren with few natural vegetation of scattered desert weeds. The coordinates of the upper left corner is 30 33 20.43E (longitude) and 30 18 03.73N (latitude), while the lower right corner is 30 33 19.46E (longitude) and 30 15 49.50N (latitude).

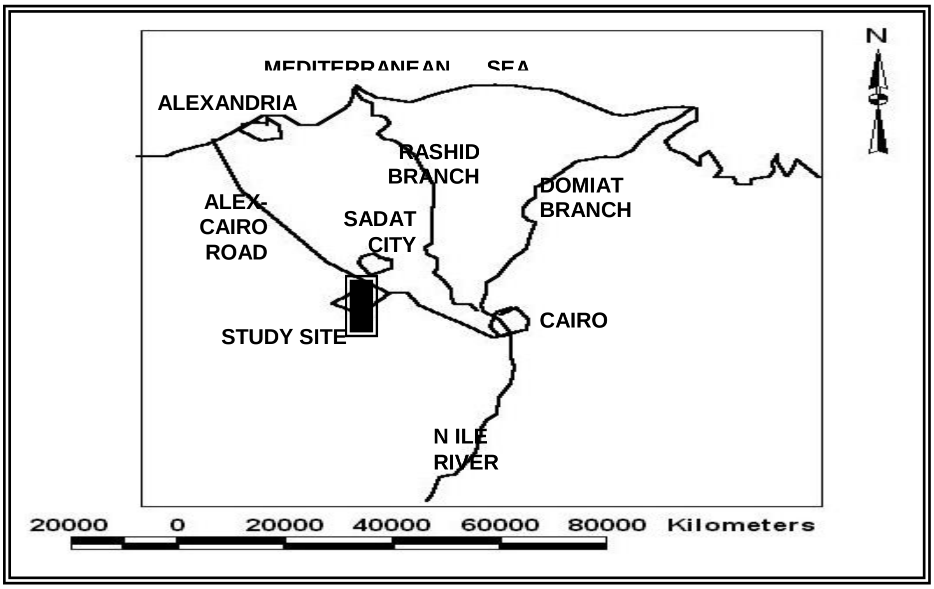

Figure (1): Sketch map of the study site location.

Climatologically Data: The data was collected from Sadat City metrological Station. The average values for the maximum, average and minimum temperature over the months of the year 2002, were 21, 12 and 5 degree, respectively. The most frequent wind speed is (2.5 – 5.5 m/s) at the day time, most of the year, while in January and March it reaches to 20.5 m/s. It's direction is NW in winter and NE or/ and E in summer. The maximum rainfall is 50 mm/year, which falls in the winter and early spring. The area has low relative humidity ranging between 20 to 30 ٪ throughout most of the year with exception of July-September (around 50 ٪(.

Soil analysis: A summary of the measured parameters and number of sampling sites for the study area are given in table 1. The area was divided to 20 sector, each represented 100 feddand. Each sector has one profile with 100 cm depth in the center and surrounding by four augers. The profiles were completely described and the representative soil samples were taken from each layer for chemical and physical analysis (Page *et al*., 1982). However, only the surface soil samples were used in this study. The analysis have been done for seven different combinations of data sets depending on the number of the surface samples as in table 2, (100 surface auger and profile, 85 out of them without vegetation, 80 surface auger, 68 surface auger without vegetated area, 20 sector (each sector has averaged of four auger sample), 20 surface sample of profiles, and 17 surface profile samples without vegetated area. In addition, 60 undisturbed cores (3 for each sector) were collected for determining the Kh. Infiltration rates were measured in the middle of each sector.

Table(1): Sites Description and Soil Analysis..

Sample Size	**Total Samples (100)**				
	Profiles		**Auger Holes**		
Numbers	**20**		**80**		
Soil Samples Analysis	Dry and Wet Color, $CaCO_3$ %, Gravel %, Coarse Sand %, Medium Sand %, Fine Sand %, Silt and Clay %, and Electrical Conductivity (EC ds/m),		$CaCO_3$ %, Organic Matter (OM%(, Cation Exchange Capacity (CEC meql/100gm), and Electrical Conductivity(EC ds/m),		
	Hydraulic Conductivity (Kh cm/h), And Infiltration Rate (cm/min)		Available Phosphorus (ppm), Available Potassium (ppm), and Available Micronutrients (Fe, Mn, Zn and Cu ppm)		
Division Type	**20 samples of all area**	**17 samples of bare soil only**	**80 sampl of all area**	**68 sample for Bare Soil**	**20 sectors averaged from 80 augers**
Total	100 (bare soil and vegetated area) and 85 (bare soil only)				

Statistical analysis: The statistical analysis were performed using the computer software program SYSTAT (SYSTAT, 1990) for the seven groups of samples. Descriptive statistics provide guidelines to judge overall spatial variability. The mean (X) and the standard deviation (SD) are measures of the center and variability around it, respectively. Larger SD values indicate larger heterogeneities in the area. Also, small range (maximum value-minimum value) indicates less variability. The coefficient of variation (CV) measures the relative variability. Warrick *et al*., 1986, classified the CV for several soil properties into four classes. These classes were low variation ($CV \leq 10$ %(, medium (between 10 to 60 %(, high (between 60 – 100 %(and very high CV values (>100 %(. The multiple regression analysis was conducted for soil properties prediction equations using the image digital numbers for each data sets. The multiple regression model is expressed by the **equation:**

$$Y_i = \beta_1 X_1 + \beta_2 X_2 + \ldots\ldots + \beta_6 X_6$$

where: Y_i is the dependant variable represents soil attributes and $\beta_1, \beta_2, \ldots\ldots \beta_6$ are the regression coefficients associated with the independent variable (digital numbers of TM bands) X_1, X_2, ……X_6. The inverse distance weight was used as a tool in geostatistical application to predict the soil properties at unmeasured sites. The resulted interpolated value is a weighted average of nearest assigned number of survey sites. Each survey point receive a weight proportional to the inverse of the squared distance from test site. So, it represents the average rate of property change with distance and used for drawing maps (Gutjahr, 1985).

Table(2): Statistical Analysis of Soil Sample for Soil properties..

Data Types	**Total Surface Points (100)**	
	Original Data	**Average Data**
Data Sets	**20** Profile Surface Point	**80** Auger surface and the averaged of them to **20** sector.
Descriptive, multiple linear Regression, and geostatistical analysis	**Properties description for each point: 15** Soil properties (table 1) and Digital Numbers in Six Bands (TM1, TM2, TM3, TM4, TM5, and TM7)	**Properties description for each point:** **10** Soil properties (table 1) and Digital Numbers in Six Bands (TM1, TM2, M3, TM4, TM5, and TM7) and the averaged data for the same bands.
Total Properties	**21** properties estimated for 20 sites.	**16** properties estimated for: 80 augers and calculated for the 20 sector sites
Total	**37 soil properties**	

Image analysis: The cloud free TM image was used in raster format for image processing analysis (ERDAS, 1997). The image analysis for the area of interest (AOI) included vegetation indices analysis and supervised and unsupervised Classification. While, the TM satellite data is expressed in units of digital numbers (DN) as they are on the computer compatible tape (CCT), they are in sex wavelength bands (TM_1, TM_2, TM_3, TM_4, TM_5, and TM_7). The ASCII data files converted to Raster Images, using ERDAS 1999 software and stacked together for mapping analysis and were used for soil properties prediction.

Mapping units: All samples locations were geo-referenced and their UTM coordinates were determined from previously registered TM image. The prediction equations derived from the statistical analysis were utilized to calculate the predicted values of each soil properties for all sample sites. Soil data base file including the estimated and predicted soil properties were kriged by inverse distance weight technique in Arc-View using the developed method of Boeringa, 2003. Arv-view software (ESRI, 1997) was used to utilize geographical information system to finalize the mapping units in vector format by grid analyst extension.

RESULTS

Spectral Signature

The green vegetation over a soil causes reduction the composite red radiance due to chlorophyll absorption, while increase the overall infrared response as a result of leaf mesophyll structure. Thus, deviations of spectral data from the bare soil line, (figure 2) in an appropriate direction, may be attributed to the presence of green biomass. In the same time, by spectral signature analysis, it was found that the natural vegetation has three levels of density, high, medium and low amount with a total 13.6 % (figure 3).

Fig2

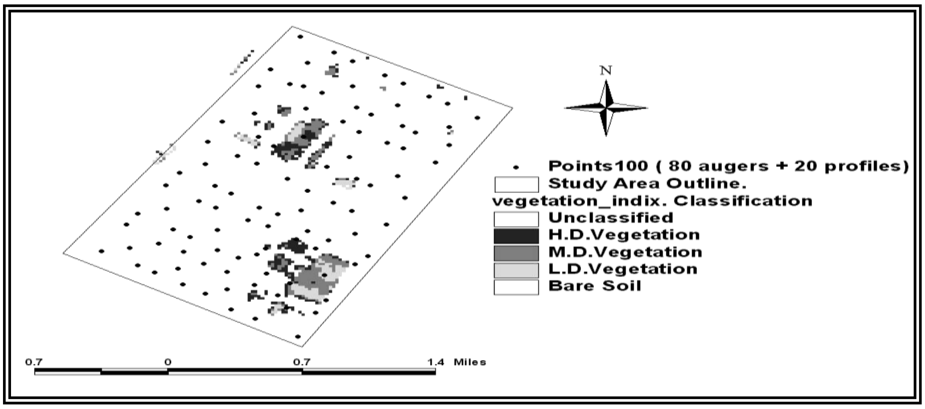

Figure (3): Sample Sites Distribution, and Vegetation Density Levels.

Soil Variability: Tables 3 and 4 present the descriptive statistics for the estimated soil surface properties. Table 3, show that the properties which have more than 60 % variability are, by decreasing sequence, $CaCO3$ %, infiltration rate, EC, gravel % and Kh. These properties (according to Warrick *et al*., 1986) has great effect on soil variability. While the sand and silt plus clay fractions as well as color components (table 5). Soil color hue has higher effect than chroma than value under both dry and wet conditions. Hue under wet condition has little more effect than that under dry condition, while chroma and value components have the opposite trend (table 6).

Table 3 : Descriptive Statistics of the auger surface studied Soil properties.

Sample Size	$CaCO_3$	CEC	EC	OM	Av_P	Av_K	Fe	Mn	Zn	Cu
Range										
80	16.06	9.43	37.35	0.05	6.64	84.20	2.00	0.60	0.73	0.33
68	15.88	9.43	37.35	0.05	5.39	84.20	2.00	0.34	0.73	0.33
SD										
80	3.83	1.74	10.4	0.01	1.37	22.62	0.40	0.07	0.17	0.07
68	3.93	1.85	10.38	0.01	1.33	22.47	0.42	0.05	0.18	0.07
CV										
80	0.68	0.26	0.78	0.36	0.29	0.33	0.18	0.27	0.30	0.22
68	0.66	0.27	0.77	0.36	0.28	0.34	0.19	0.23	0.31	0.23

Table 4: Descriptive Statistics of the profile surface studied Soil Properties.

Sample Size	$CaCO_3$	EC	Gravel	Coarse Sand	Medium Sand	Fine Sand	Silt+ Clay	Kh	Infit. Rate
Range									
20	18.11	37.60	26.40	11.50	32.10	37.70	5.10	37.81	0.447
17	*18.11*	*37.60*	*24.20*	*11.50*	*32.10*	*37.70*	*2.90*	*37.81*	*.448*
SD									
20	5.26	12.23	8.92	3.23	9.18	10.15	12.23	9.83	0.14
17	*5.49*	*12.80*	*8.63*	*3.24*	*9.46*	*10.50*	*0.82*	*9.57*	*0.15*
CV									
20	1.07	0.96	0.28	0.46	0.38	0.15	0.41	0.64	1.01
17	*1.12*	*1.02*	0.78	*0.45*	*0.38*	*0.16*	*0.32*	*0.56*	*1.02*

Table(5): Descriptive Statistics of the surface profiles color components.

Dry and Wet Condition	Descriptive Parameters					
Color Component	**Minimum**	**Maximum**	**Mean**	**Variance**	**SD**	**CV**
Hue_Dry	2.50	10.00	6.88	11.10	3.33	0.48
Value_Dry	5.00	8.00	6.25	0.83	0.91	0.15
Chroma_Dry	2.00	8.22	6.20	4.59	2.14	0.35
Hue_Wet	2.50	10.00	6.75	11.91	3.45	0.51
Value_Wet	4.00	6.00	5.30	0.33	0.57	0.11
Chroma_Wet	4.00	8.00	5.75	2.51	1.59	0.28

Data of the collected digital numbers for four data sets without vegetation back ground (table 6) show that the CV's for all bands ranged between 0.04 to 0.08 and has no effect on soil variability. On the other hand, the areas with vegetation show some little effect on variability and ranged between 0.07 and 0.20. Table 7, shows the descriptive statistics for averaged data of 20 sectors. Results indicate that $CaCO_3$ ٪)CV=0.58) and EC (CV= 0.67) had the highest effect on soil variability, while the rest of the properties and digital numbers had small effect or no effect.

Table 6: Descriptive Statistics of the Original image DN's with sample size.

Sample Size	TM1	TM2	TM3	TM4	TM5	TM7
						Range
80	56.00	71.00	102.00	53.00	79.00	83.00
68	*42.00*	*48.00*	*61.00*	*45.00*	*49.00*	*49.00*
20	34.00	54.00	96.00	42.00	88.00	96.00
17	*15.00*	*17.00*	*32.00*	*25.00*	*25.00*	*28.00*
						SD
80	7.48	10.45	16.59	10.37	14.31	14.85
68	*5.88*	*7.67*	*11.74*	*9.72*	*10.05*	*9.17*
20	10.03	15.11	25.56	12.23	22.80	25.64
17	*4.32*	*5.72*	*10.56*	*8.69*	*8.18*	*8.09*
			CV			
80	0.07	0.10	0.11	0.09	0.09	0.11
68	*0.06*	*0.07*	*0.08*	*0.08*	*0.06*	*0.07*
20	0.10	0.14	0.18	0.10	0.16	0.20
17	*0.04*	*0.05*	*0.07*	*0.07*	*0.05*	*0.06*

Table 7:Descriptive Statistics of 20 sectors.

Soil Properties	Minimum	Maximum	Mean	Variance	SD	CV
$CaCO_3$ ٪	0.71	10.89	5.63	6.81	3.25	0.58
CEC meq./100 gm soil	4.78	10.02	13.28	10.56	1.43	0.21
EC ds/m	0.81	25.75	6.81	2.04	8.92	0.67
OM ٪	0.03	0.06	0.04	0.001	0.01	0.31
Ave_P ppm	3.12	6.53	4.67	1.20	1.09	0.23
Ave_K ppm	37.00	109.75	67.68	383.45	19.58	0.29
Fe ppm	1.33	2.67	2.26	0.10	0.32	0.14
Mn ppm	0.12	0.33	0.25	0.002	0.04	0.17
Cu ppm	0.19	0.43	0.32	0.003	0.05	0.17
Zn ppm	0.26	0.82	0.57	0.02	0.15	0.25
			Digital numbers			
Average_TM_1	93.50	121.75	105.09	29.82	5.46	0.05
Average_TM_2	90.50	129.50	107.68	60.73	7.79	0.07
Average_TM_3	118.75	173.00	144.76	157.07	12.53	0.09
Average_TM_4	109.50	141.75	120.83	73.99	8.60	0.07
Average_TM_5	134.25	172.50	151.39	98.08	9.90	0.07
Average_TM_7	111.00	149.75	131.90	86.69	9.31	0.07

Soil Properties Predictions: Predictions of surface soil properties were based on the pixel values as digital numbers (DN's) in all six bands of TM image, that was collected by ERDAS software using UTM coordinate system for all data points. The analysis have been done for five different set of data (tables 8, 9, 10 and 11). Calcium carbonate ٪ prediction was higher for the sites without vegetation than that with vegetation. Also, the predicted ability (R) increase with increasing sample size. This ability increase for the same data set size with the sector data set, which used the averaged digital numbers than that for profile points (table 8).

Table 8: Multiple linear regression of $CaCO_3$ ٪ and EC.

	Prediction Equations	(R)	R^2
	Data set For $CaCO_3$ ٪		
100	$0.07TM_1 – 0.41TM_2 + 0.13TM_3 + 0.14TM_4 - 0.10TM_5 + 0.17TM_7$	(0.819)	0.671
85	$-0.09TM_1 – 0.29TM_2 + 0.41TM_3 - 0.26TM_4 - 0.04TM_5 + 0.19TM_7$	(0.830)	0.689
80	$0.07TM_1 – 0.48TM_2 + 0.20TM_3 + 0.18TM_4 - 0.2TM_5 + 0.22TM_7$	(0.858)	0.736
68	$-0.04TM_1 - 0.38TM_2 + 0.32TM_3 + 0.002TM_4 - 0.21TM_5 + 0.28TM_7$	(0.867)	0.752
20_pro	$0.55TM_1 – 0.82TM_2 + 0.24TM_3 - 0.30TM_4 + 0.42TM_5 - 0.20TM_7$	(0.705)	0.497
20_sec	$- 0.56TM_1 + 0.42TM_2 - 0.65TM_3 + 0.46TM_4 - 0.21TM_5 + 0.69TM_7$	(0.722)	0.521
17	$0.49TM_1 – 1.06TM_2 + 1.60TM_3 – 1.78TM_4 + 0.70TM_5 - 0.44TM_7$	(0.744)	0.554
	Data set For EC		
100	$- 0.05TM_1 - 0.27TM_2 – 0.13TM_3 + 0.35TM_4 - 0.07TM_5 + 0.26TM_7$	(0.780)	0.608
85	$- 0.10TM_1 + 0.03TM_2 – 0.12TM_3 + 0.14TM_4 - 0.11TM_5 + 0.28TM_7$	(0.776)	0.602
80	$- 0.11TM_1 - 0.32TM_2 – 0.07TM_3 + 0.48TM_4 - 0.16TM_5 + 0.28TM_7$	(0.797)	0.635
68	$0.01TM_1 – 0.14TM_2 - 0.54TM_3 + 0.96TM_4 - 0.39TM_5 + 0.38TM_7$	(0.797)	0.635
20_pro	$1.83TM_1 – 1.90TM_2 + 0.73TM_3 – 1.00TM_4 + 0.65TM_5 - 0.44TM_7$	(0.748)	0.560
20_sec	$- 0.13TM_1 + 0.45TM_2 – 1.18TM_3 + 1.00TM_4 – 1.13TM_5 + 1.40TM_7$	(0.762)	0.581
17	$1.43TM_1 – 1.54TM_2 + 3.72TM_3 – 4.11TM_4 + 1.18TM_5 – 1.01TM_7$	(0.781)	0.610

Table 9:Multiple linear regression of soil surface color components.

Data Set	Prediction Equations	(R)	R^2
Hue in dry condition			
20_profile	$0.17TM_1+ 0.32TM_+ - 0.06TM_3-0.47TM_4-0.61TM_5 – 0.55TM_7$	(0.918)	0.843
20_sector	$0.79TM_1-1.6TM_++0.65TM_3-0.05TM_4-0.1TM_5 +0.18TM_7$	(0.915)	0.837
17	$0.08TM_1+0.32TM_++0.72TM_3-1.43TM_4+0.83TM_5 –0.72TM_7$	(0.932)	0.867
Hue in wet condition			
20_profile	$0.21TM_1+0.16TM_+-0.0008TM_3-0.52TM_4+0.68TM_5–0.55TM_7$	(0.913)	0.834
20_sector	$0.58TM_1-1.36TM_++0.53TM_3-0.07TM_4-0.03TM_5+0.22TM_7$	(0.910)	0.828
17	$0.08TM_1+0.32TM_++0.72TM_3-1.43TM_4-0.83TM_5–0.72TM_7$	(0.932)	0.867
Value in dry condition			
20_profile	$0.18TM_1-0.31TM_++0.02TM_3+0.09TM_4-0.01TM_5+0.06TM_7$	(0.993)	0.986
20_sector	$0.14TM_1-0.121TM_+-0.009TM_3+0.07TM_4-0.001TM_5–0.01TM_7$	(0.991)	0.982
17	$0.2TM_1-0.31TM_+-0.18TM_3+0.32TM_4-0.05TM_5+0.1TM_7$	(0.994)	0.988
Value in wet condition			
20_profile	$0.09TM_1-0.1TM_+-0.02TM_3+0.06TM_4-0.003TM_5+0.02TM_7$	(0.996)	0.992
20_sector	$0.05TM_1+0.04TM_+-0.05TM_3-0.0001TM_4+0.07TM_5–0.06TM_7$	(0.996)	0.992
17	$0.1TM_1-0.11TM_+-0.13TM_3+0.18TM_4–0.01TM_5+0.04TM_7$	(0.995)	0.990
Chroma in dry condition			
20_profile	$0.14TM_1+0.15TM_++0.03TM_3+0.24TM_4–0.27TM_5+0.3TM_7$	(0.950)	0.903
20_sector	$0.7TM_1-1.14TM_++0.52TM_3+0.04TM_4–0.14TM_5–0.02TM_7$	(0.950)	0.903
17	$0.02TM_1+0.36TM_++0.55TM_3-0.87TM_4+0.30TM_5–0.42TM_7$	(0.965)	0.931
Chroma in wet condition			
20_profile	$0.43TM_1-0.38TM_++0.26TM_3-0.29TM_4+0.26TM_5-0.3TM_7$	(0.970)	0.941
20_sector	$0.46TM_1-0.75TM_++0.29TM_3+0.12TM_4–0.14TM_5+0.01TM_7$	(0.967)	0.935
17	$0.34TM_1-0.17TM_++0.46TM_3-0.57TM_4+0.25TM_5-0.36TM_7$	(0.976)	0.953

Table 10 : Multiple linear regression of some soil surface properties.

Data Set	Prediction Equations	(R)	R^2
			Available K
80	$0.97TM_1 – 2.25TM_2 – -0.65TM_3 + 0.89TM_4 + 0.98TM_5 + 0.35TM_7$	(0.953)	0.908
68	$0.07TM_1 - 1.04TM_2 + 0.19TM_3 – 0.55TM_{4+}. 0.76TM_5 + 0.70TM_7$	(0.951)	0.904
			Available P
80	$0.05TM_1 + 0.03TM_2 – 0.08TM_3 + 0.04TM_4 – 0.0006TM_5 + 0.02TM_7$	(0.961)	0.924
68	$0.1TM_1 – 0.03TM_2 – 0.2TM_3 + 0.23TM_4 – 0.05TM_5 + 0.05TM_7$	(0.965)	0.931
			Cation exchange Capacity
80	$0.09TM_1 – 0.12TM_2 + 0.04TM_3 + 0.01TM_4 + 0.02TM_5 + 0.0001TM_7$	(0.970)	0.941
68	$0.05TM_1 – 0.12TM_2 + 016TM_3 – 0.15TM_4 + 0.06TM_5 + 0.002TM_7$	(0.968)	0.937
			Organic Matter %
80	$-0.00004TM_1 – 0.0009TM_2 – 0.0007TM_3 + 0.0008TM_4 + 0.0008TM_5 + 0.0002TM_7$	(0.954)	0.910
68	$0.0003TM_1 – 0.00093TM_2 –.0.002TM_3 + 0.02TM_4 + 0.00065TM_5 + 0.0003TM_7$	(0.955)	0.912
			Available Fe
80	$0.019TM_1 + 0.009TM_2 – 0.02TM_3 + 0.03TM_4 - 0.0009TM_5 + 0.001TM_7$	(0.985)	0.970
68	$0.003TM_1 + 0.02TM_2 – 0.02TM_3 + 0.02TM_4 + 0.003TM_5 + 0.0009TM_7$	(0.983)	0.966
			Available Zn
80	$0.0004TM_1 – 0.002TM_2 – 0.003TM_3 + 0.01TM_4 – 0.006TM_5 + 0.004TM_7$	(0.962)	0.925
68	$-0.006TM_1 + 0.001TM_2 + 0.01TM_3 - 0.01TM_4 + 0.0003TM_5 + 0.003TM_7$	(0.961)	0.924
			Available Mn
80	$0.003TM_1 - 0.004TM_2 - 0.002TM_3 + 0.006TM_4 - 0.005TM_5 + 0.004TM_7$	(0.968)	0.937
68	$0.002TM_1 - 0.006TM + 0.007TM_3 - 0.003TM_4 - 0.003TM_5 + 0.003TM_7$	(0.980)	0.960
			Available Cu
80	$0.004TM_1 - 0.009TM_+ + 0.002TM_3 + 0.005TM_4 - 0.003TM_5 + 0.003TM_7$	(0.979)	0.958
68	$0.003TM_1 - 0.009TM_+ + 0.008TM_3 - 0.003TM_4 - 0.001TM_5 + 0.003TM_7$	(0.977)	0.955
			Gravel %
20_pro.	$1.22TM_1 + 0.11TM_+ + 0.53TM_3 - 1.73TM_4 + 1.47TM_5 - 1.65TM_7$	(0.837)	0.701
20_sec.	$1.67TM_1 - 3.01TM_+ + 1.45TM_3 - 0.45TM_4 + 0.005TM_5 - 0.02TM_7$	(0.807)	0.651
17	$0.61TM_1 + 1.54TM_+ + 1.70TM_3 - 3.48TM_4 + 1.44TM_5 - 2.03TM_7$	(0.894)	0.799
			Coarse Sand %
20_pro.	$-0.37TM_1 + 0.34TM_+ - 0.45TM_3 + 0.07TM_4 + 0.50TM_5 - 0.07TM_7$	(0.932)	0.869
20_sec.	$0.23TM_1 - 0.12TM_+ + 0.08TM_3 - 0.56TM_4 + 0.76TM_5 - 0.50TM_7$	(0.926)	0.857
17	$-0.48TM_1 + 0.74TM_+ - 0.54TM_3 + 0.15TM_4 + 0.31TM_5 - 0.70TM_7$	(0.927)	0.859
			Medium Sand %
20_pro.	$-0.89TM_1 + 0.63TM_+ - 0.51TM_3 + 1.04TM_4 – 0.67TM_5 + 0.75TM_7$	(0.950)	0.903
20_sec.	$-1.96TM_1 + 3.27TM_+ - 1.34TM_3 + 0.69TM_4 – 0.80TM_5 + 0.83TM_7$	(0.955)	0.912
17	$--0.67TM_1 - 0.12TM_+ - 0.36TM_3 + 0.97TM_4 – 0.38TM_5 + 0.77TM_7$	(0.948)	0.899
			Fine Sand %
20_pro.	$2.68TM_1 - 1.31TM_+ + 0.26TM_3 - 1.04TM_4 + 1.20TM_5 - 1.27TM_7$	(0.991)	0.982
20_sec.	$4.67TM_1 - 6.48TM_+ + 2.05TM_3 + 0.12TM_4 + 0.22TM_5 - 0.54TM_7$	(0.990)	0.980
17	$2.39TM_1 - 0.30TM_+ - 0.23TM_3 - 0.80TM_4 + 0.96TM_5 - 1.28TM_7$	(0.990)	0.980
			Silt and Clay %
20_pro.	$0.14TM_1 - 0.20TM_+ - 0.009TM_3 - 0.04TM_4 + 0.16TM_5 - 0.07TM_7$	(0.940)	0.884
20_sec.	$0.35TM_1 - 0.54TM_+ + 0.14TM_3 + 0.08TM_4 – 0.03TM_5 - 0.003TM_7$	(0.948)	0.891
17	$0.08TM_1 - 0.04TM_+ + 0.15TM_3 - 0.1\ 8TM_4 + 0.08TM_5 - 0.10TM_7$	(0.957)	0.916
			Kh
20_pro.	$0.55TM_1 - 0.39TM_+ - 0.66TM_3 - 0.67TM_4 + 1.19TM_5 - 0.007TM_7$	(0.904)	0.817
20_sec.	$-2.02TM_1 + 2.44TM_+ - 2.14TM_3 + 0.37TM_4 – 0.27TM_5 + 2.05TM_7$	(0.910)	0.828
17	$1.12TM_1 - 1.95TM_+ - 1.60TM_3 + 0.44TM_4 + 1.73TM_5 + 0.25TM_7$	(0.938)	0.880
			Infiltration Rate.
20_pro.	$0.04TM_1 - 0.05TM_+ + 0.02TM_3 - 0.006TM_4 + 0.001TM_5 + 0.004TM_7$	(0.779)	0.607
20_sec.	$0.02TM_1 - 0.02TM_+ - 0.002TM_3 - 0.0002TM_4 - 0.002TM_5 + 0.007TM_7$	(0.757)	0.573
17	$0.04TM_1 - 0.05TM_+ - 0.04TM_3 + 0.06TM_4 - 0.01TM_5 + 0.02TM_7$	(0.937)	0.878

Table 11:Mapping Classes Accuracy of $CaCO_3$ % and EC.

Class Id	Original EC classes %	Predicted EC classes %	Accuracy %	Original $CaCO_3$% classes %	Predicted $CaCO_3$% classes %	Accuracy %
1	34.13	34.69	98.39	26.59	28.25	*94.12*
2	22.47	25.58	87.84	37.83	32.09	*84.83*
3	31.57	27.34	86.60	30.39	33.52	*90.66*
4	11.43	12.00	95.25	4.95	5.90	*83.90*
5	0.40	0.39	97.50	0.24	0.24	*100.00*
Over all accuracy %	*93.12*			*90.70*		
EC Differences (predicted-original)				$CaCO_3$% Difference (predicted-original)		
Negative	*6.87%*	*Total accuracy 88.70 %*		*3.04%*	*Total accuracy 91.45%*	
Equal Difference	*88.70%*			*91.45%*		
Positive	*3.98%*			*5.06%*		

As for, the electrical conductivity data show the same predicted ability except for the large sample size where there was no difference between the prediction with or without vegetation effect. All other surface chemical properties were highly predicted using Satellite digital numbers (R > 0.95 and R^2 >0.90). Predicted available potassium, CEC, and available iron, zinc and cupper for vegetated area were very little higher than that for non-vegetated area. While available phosphorous, organic matter and available manganese has the opposite predicted ability trend. Also, the prediction power (R^2) decrease in the following sequence: iron, cupper, manganese, CEC, available phosphorus, available zinc, organic matter and available potassium. Concerning the color components (table 9), chroma and hue have R and R^2 more than 0.991, 0.950 and 0.910 and 0.982, 0.903 and 0.828, respectively. Sets without vegetation have higher prediction ability than those with vegetation for dry and wet conditions in all soil color components except for value in the wet condition. Table 10 shows that the highest predicted ability was for fine sand, while, the lowest was for infiltration rate. The averaged data sets (sectors) give highest R and R^2 than the original data sets (profile points) for medium sand, the summation of silt and clay and hydraulic conductivity. The opposite relationships was observed for the rest soil surface properties.

Spatial Distribution of Soil Properties

Geostatistical analysis by inverse distance technique was carried out to map the spatial distribution of the predicted $CaCO_3$ % and EC (figures 4c and 6c) and compare it to the original data (figures 4b and 6b). $CaCO_3$% and EC were chosen because they are the most effective soil properties on soil variability. Also, maps figures 4a and 6a show the extend area surrounding the sampling area, which could be extended for 6.5 to 20 times area more with the same accuracy, because the sampling area usually represent 15 % of the total area for GIS and remote sensing analysis. The mapping classes accuracy ranged for $CaCO_3$% and EC between 83.90 to 100 % and 86.60 to 98.39 %, while the average accuracy over all classes are 90.70 to 91.45 % and 88.70 to 93.12 %, respectively, (fig. 5 and 7 and table 11).

Fig4a,4b

4c,5,6a

6b,6c,7

Mapping Units

Soil analysis as well as soil variability analysis indicate that the study area soils differ mainly in their $CaCO_3$% and EC. Using GIS techniques and taking both soil properties as a main criteria to create a soil mapping units map, five units were recognized as shown in figures 8 and 9. They represent the spatial distribution of the soil mapping units mapped from the original and predicted classes of $CaCO_3$% and EC. First mapping unit has EC ranged between 0.0 to 2.0 ds/m and $CaCO_3$% from 0.0 to 4.0 %. Second one has EC and $CaCO_3$% ranged from 2.0 to 4.0 and 2.00 to 8.0, respectively.

Third one has EC between 4.0 to 8.0 and $CaCO_3$% from 8.0 to 12.0 % . The last two mapping units has EC more than 16 ds/m. In the same time, fourth one has $CaCO_3$% ranged from 4.0 to 12.0 %, while the last one has more than 16.0 % The accuracy of all mapping units (table 12) ranged between 81.38 % to 99.64 % with over all average accuracy 87.88 %.

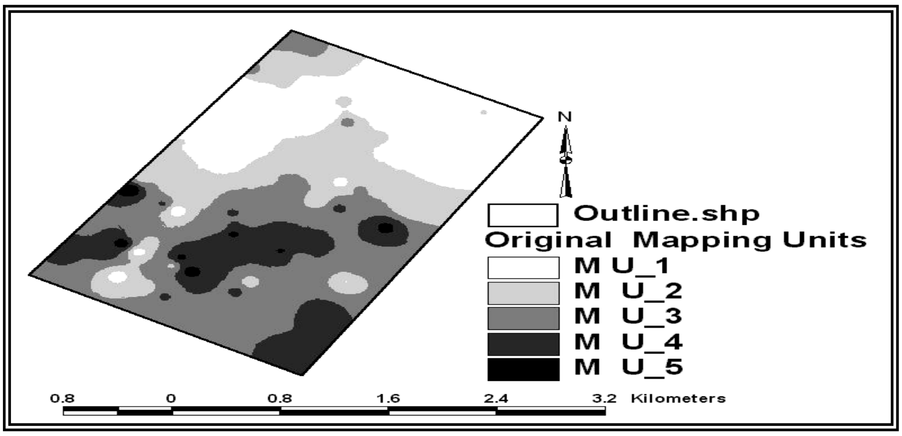

Figure 8: Mapping Units from original values of CaCO3 and EC Classes.

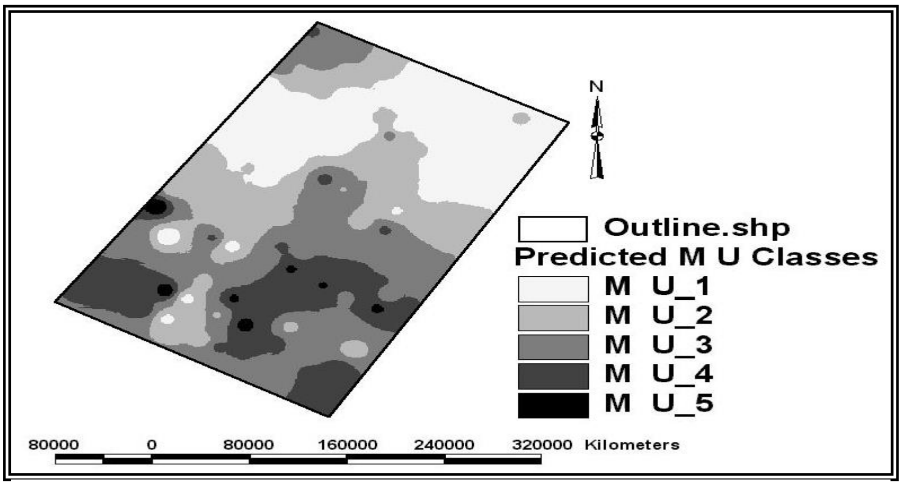

Figure 9: Mapping Units from Predicted values of CaCO3 and EC Classes

Table 12: Mapping Units Accuracy.

Mapping Units ID	٪ of each MU from original values	٪ of each MU from predicted values	٪ of Mapping Units Accuracy	٪ of *Over All Accuracy*
MU_1	25.56	28.11	90.93	**87.88**
MU_2	19.51	19.44	99.64	
MU_3	17.74	21.80	81.38	
MU_4	31.72	25.97	81.87	
MU_5	*5.47*	*4.68*	*85.56*	

CONCLUSION

Soil data base of the soil survey is time consuming and often costly, but when using the remote sensing for predicting soil properties and geographical information system for mapping such properties and soil mapping units may provide a cost effective and efficient alternative tools for more detailed soil survey. In this research, the TM digital numbers were used successfully to predicted all the studied soil properties of bare desert soil in the sampling area (2000 feddans) close to Sadat City region. The data showed that the spatial distribution comparisons of the predicted values of the most effective soil properties in the area, CaCO3 % and EC, with the original data had higher average accuracies more than 89 and 93%, respectively. Also, the average accuracy was more than 89% for soil mapping units of that area. That accuracy could be applied for mapping larger area in the same region. Therefore, the TM image may provide a reasonable tool for predicting soil properties and mapping soil mapping units in such bare desert soils.

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تحليل بيانات الأقمار الصناعية العددية لتقدير صفات التربة ورسم وحدات التربة الخرائطية للأراضي الصحراوية الجرداء بمنطقة السادات بمصر

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تهدف هذه الدراسة الى محاولة التنبؤ بصفات التربة و رسم وحداتها و ذلك عن طريق تحليل صور الأقمار الصناعية. و تقع منطقة الدراسة عند الكيلو 84 - 86 من يسار الطريق الصحراوي (القاهرة-الاسكندر يه) وعلى مسافة 5 كيلو مترات إلى غرب الطريق. تم تقسيم المساحة إلى 20 جزء بمساحة 100 فدان لكل جزء. تم حفر قطاع ممثل لكل جزء في مركزة وحول كل قطاع وعلى مسافات متساوية تم حفر 4 أوجر. تم إجراء بعض التحليلات الطبيعية والكيماوية لعينات التربة ورسم خرائطها باستخدام التحليل الفراغي باستخدام برامج المعلومات الجغرافية (GIS). كما تم تحليل صورة القمر الصناعي الأمريكي (TM) لعام 1999 واستخلاص البيانات الرقمية الخاصة بمواقع كل العينات بعد تحديد إحداثيات كل منها باستخدام الخرائط الطبوغرافية للمنطقه ونظام UTM للإحداثيات.

أوضحت تحليلات صورة القمر الصناعي أن المساحة أغلبها أرض جرداء (86.4٪) وبها جزء تغطيه النباتات الطبيعية بكثافات مختلفة (ثلاثة مستويات تمثل 13.6 ٪) . يقع في المساحات التي تغطيها النباتات 12 عينة أوجر و 3 قطاعات. لذا أمكن تقسيم البيانات إلى ستة مجا ميع هي 100, 85, 80, 68 , 20 و17 عينه سطحيه بالاضافه إلى المجموعه السابعة وتشمل متوسطات عينات الأوجر لعشرون قطعة. التحليلات الإحصائية و الفراغية للبيانات المستخدمة في مجا ميع مختلفة العدد أوضحت أن وجود النباتات الطبيعية لم يؤثر على درجة اختلافات خصائص التربة بسبب انتشارها الغير متجانس وتوزيعا العشوائي مما يبرز تأثير خلفية التربة خاصة على بيانات الصورة. المجموعتين 80 و 68 عينة من مواقع الأوجر. أظهرت النتائج المتحصل عليها أن أكثر الخصائص تأثيراً على اختلافات التربة هما درجة الملوحة (EC) ونسبة كربونات الكالسيوم الكلية حيث زاد معامل الاختلاف لهما عن 60٪ وباقي الخصائص مثل السعه التبادلية الكاتيونية و المادة العضوية و العناصر المتاحة الكبرى مثل الفوسفور والبوتاسيوم والصغرى مثل الحديد والمنجنيز والزنك والنحاس حيث كان لها تأثير متوسط على درجة التجانس حيث تراوح معامل الاختلاف بين10 ٪إلى 60٪. في حين أنة فى المجاميع 20 و 17 عينة المأخوذة من مواقع القطاعات تم

تقسيم خصائص التربة الى ثلاثة مجاميع تبعا لتأثيرها على درجة اختلاف التجانس. المجموعة الأولى كان لها معامل اختلاف أكبر من 100٪ أي تأثير عالي جدا وتشمل نسبة كربونات الكالسيوم الكلية ومعدل التسرب و درجة الملوحة (EC) . المجموعة الثانية ذات معامل اختلاف يتراوح بين 100 – 60 ٪ أي أنها ذات تأثير عالي وتشمل نسبة تغطية السطح بالحصى و معامل التوصيل الهيدروليكي. في حين أن المجموعة الأخيرة ذات تأثير متوسط ومعامل اختلاف يتراوح بين 60 – 10٪ وتشمل باقي الصفات الأخرى مثل النسبة المئوية لمجموع السلت والطين وكذلك الرمل الناعم والمتوسط والخشن.

أظهرت النتائج الخاصة بالتحليل الإحصائي المتعدد الارتداد (multi-regression) لتقدير صفات التربة من البيانات الرقمية الخاصة للحزم الضوئية الستة لصورة القمر الصناعي إمكانية استخدامها بنجاح في التنبؤ بخصائص التربة المختلفة لتلك المنطقة الصحراوية حيث تراوحت قيم معامل التقدير (R) بين 0.705-0.867 لكربونات الكالسيوم الكلية و 0.748 – 0.797 لدرجة الملوحة و0.910-0.996 لمكونات اللون و 0.803- 0.991 لحبيبات الحصى والرمل بينما العناصر المغذية الكبرى والصغرى فقد تراوح المعامل بين0.951 – 0.985 فى حين كان لمعامل التوصيل الهيدروليكى ومعدل التسرب بين 0.757– 0.938 .

كذلك تم رسم خرائط وحدات التربة باستخدام التحليل الجيوإحصائى لخصائص التربة الأكثر تأثيرا على الاختلافات مثل كربونات الكالسيوم الكلية والملوحة الأصلية والمقدرة باستخدام الحزم الطيفية للقمر الأمريكي . وقد أوضحت الخرائط أنه دقة رسم وحدات كربونات الكالسيوم الكلية تراوحت بين 83.99 ٪ و96.26٪ بمتوسط دقة قيمته 89.97٪ بينما دقة رسم وحدات الملوحة تراوحت بين86.61٪ و 98.40٪ بمتوسط دقه بلغ 93.03 ٪.في حين أن دقة رسم الوحدات الخرائطية للتربة تراوحت بين 81.34٪ إلى 99.93٪ بمتوسط دقة 87.82 ٪. وتسهم هذه الدراسة إلى إبراز أهمية استخدام تكنولوجيا الاستشعار عن بعد ونظم المعلومات الجغرافية في تقدير خواص التربة للمناطق الصحراوية الواسعة لتوفير الجهد والوقت والمال مع إعطاء الدقة العالية في استخدامهما لمساعدة متخذي القرار في وضع خطط التنمية الزراعية لتلك المناطق.