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Predicition of Soils Based on Textural Differences by means of Vis-NIR Spectroscopy

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1.Introduction

Soil Texture, that is, a soil's primary particle size distribution, soil water transport and storage, gas exchange, rooting depth, soil biological activity and organic matter storage is an extremely important (basic) soil property (Schenk and Jackson, 2005). Use of vis-NIR spectroscopy is more economical and time saving in predicting soil properties (such as texture). The aim of the study is to predict some soil properties, especially soil particle size (sand, silt and clay) and cation exchange capacity with vis-NIR spectroscopy.

2.Material and Methods

2.1. Study Area and General Properties of Soil Series

The study was conducted in the Çukurova region located in the eastern Mediterranean (between 652467 East; 4080305 North and 728097 East ; 4053751 North in WGS84 UTM Zone 36N.) (Fig. 1) and the land use was defined during sampling.

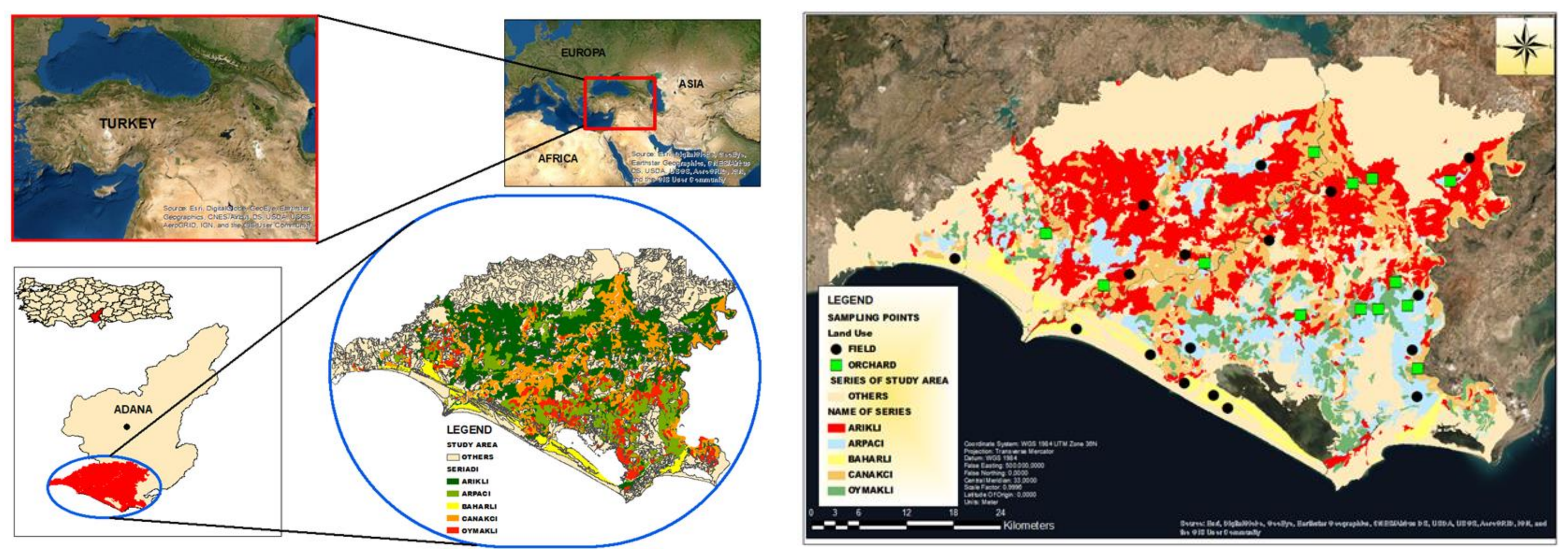

Fig 1. Geographic location of study area (right) and distribution of selected series and land uses in the study area (left).

The summers are hot and dry, and winters are wet and mild. The mean annual precipitation is 680 mm, and the mean annual temperature is 19.5 °C. Wheat, corn, cotton, soybean, peanut as well as citrus fruits are the main products cultivated intensively in the region. 20 different soil series were defined by Dinç et al. (1995) within the region. Among these soil series, Arıklı, Arpacı, Çanakçı, Oymaklı and Baharlı soil series based on different textural distribution and soil colors were selected for this study (Fig 2.) and their taxonomic levels is shown below (Table1).

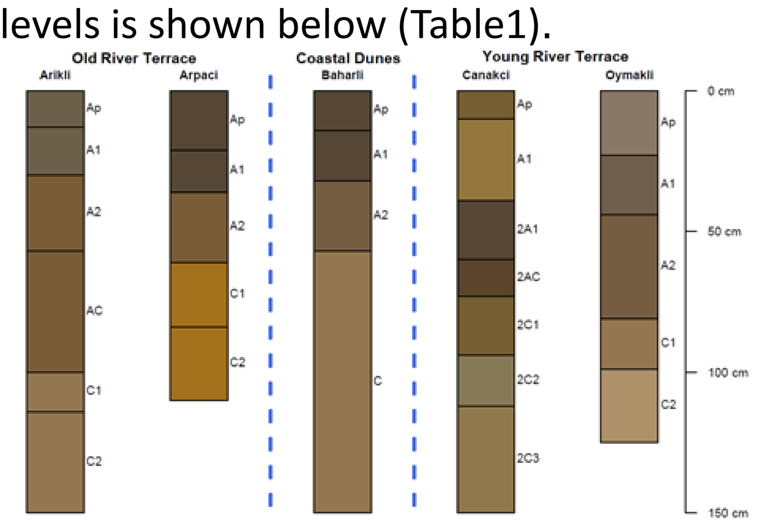

Fig 2. Physiographic units of selected series

Table 1. Taxonomic levels of selected series

SOIL SERIES	SOIL TAXONOMY(Soil Survey Staff, 1975)				FAO/ UNESCO (1974)
	Subgroup	Great Group	Suborder	Order	
Arıklı	Entic Chromoxerert	Chromoxerert	Xerert	Vertisol	Chromik Vertisol
Arpacı	Aquic Xerofluvent	Xerofluvent	Fluvent	Entisol	Calcaric Fluvisol
Baharlı	Typic Xeropsamment	Xeropsamment	Psamment	Entisol	Eutric Regosol
Çanakçı	Typic Xerofluvent	Xerofluvent	Fluvent	Entisol	Calcaric Fluvisol
Oymaklı	Typic Xerofluvent	Xerofluvent	Fluvent	Entisol	Calcaric Fluvisol

2.2. Soil Sampling and vis-NIR Analyses

Soil samples were collected at six points in each series from surface (0.0-0.3 m) and sub-surface (0.3-0.6 m). In total, 60 soil samples were collected at 30 different sampling points. In these soil samples, texture and cation exchange capacity (CEC) were analyzed.

The visible-near infrared (vis-NIR) spectra of air-dried soil samples placed on small transparent plates (20-30 g) and were scanned using a portable Analytical Spectral Devices (ASD) FieldSpec®3 (PAN Analytical B·V, Boulder, CO, USA), covering 700 nm (3 nm resolution), 1400 nm and 2100 nm (6 nm resolution), at the range from 350 nm to 2500 nm.

2.3. Vis-NIR spectra pre-processing and selection of dataset

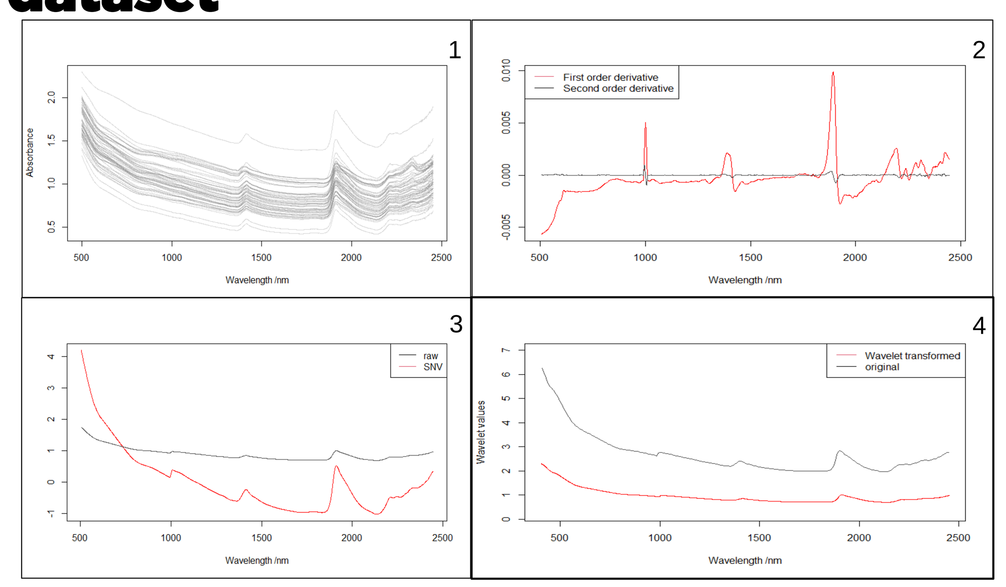

Fig.3 Vis –NIR spectra pre-processing: 1. [log10 (1/R)] (Abs), 2.SG (Savitzky-Golay), 3.SNV(standard normal variate) and 4.Wavelet transformed, respectively.

1. The vis–NIR spectra were preprocessed as follows: (i) The reflectance spectra were converted into pseudo-absorbance spectra [log10 (1/R)] (Abs)
2. The Savitzky–Golay filter with a window size of 11 nm and a polynomial order of 2 was applied to smoothen the spectra (Savitzky and Golay, 1964)

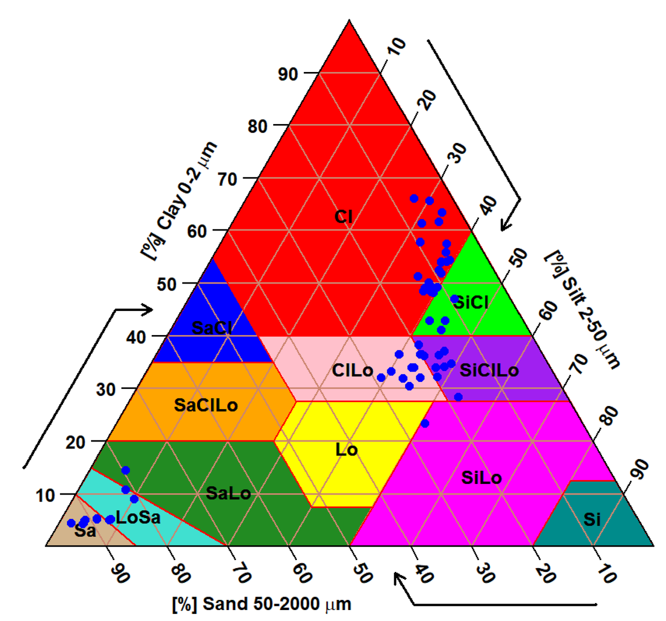

Fig.4 Demonstration of collected soil samples in texture triangle

3. The vis–NIR spectra were trimmed to 500–2450 nm to remove high signal to-noise ratio, overtones and alterations from both boundaries of the range recorded by the sensor

4. The standard normal variate transformation (SNV) was used to normalize the spectra before further analysis. The "soilspec" package (Wadoux et al., 2021) was applied for all the vis-NIR spectral pre-processing in R version 4.0.5 (R Core Team, 2021).

3.Result and Discussion

Sand, Silt, Clay and CEC varied between 3.10% and 93.50%, 2% and 53.70%, 4.40% and 66.20%, and 6.85 meq.100 g-1 and 31.67 meq.100 g-1, respectively. The CV of the indicators is high due to the sampling of soil series with different characteristics in the study area (Table2).

Table 2. Descriptive statistics of soil properties in the study

Soil properties	Unit	Min	1st Qu.	Median	Mean	3rd Qu.	Max.	CV
Sand	%	3.10	9.42	16.55	29.02	25.40	93.50	104.26
Silt	%	2.00	32.30	38.90	33.73	43.60	53.70	44.25
Clay	%	4.40	31.62	36.90	37.25	51.45	66.20	49.39
CEC	meq. 100 g^{-1}	6.85	15.73	19.21	19.64	25.16	31.67	33.03

CEC: Cation exchange capacity, CV: Coefficient of variation

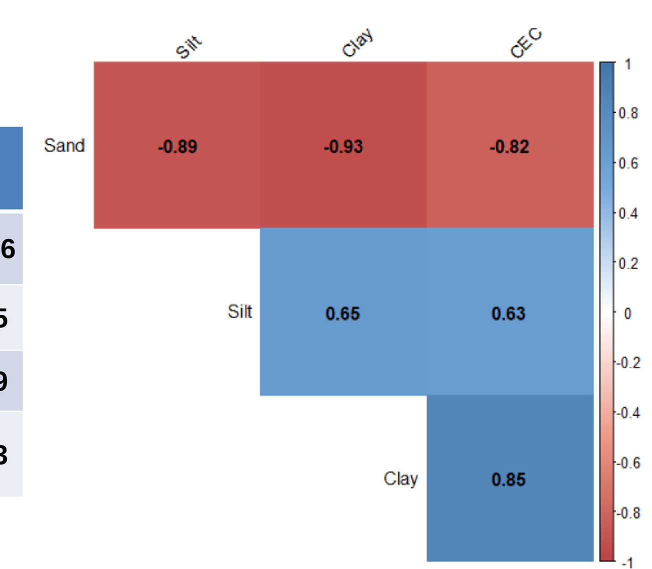

Fig 5. Correlogram of selected soil properties

All of soil properties have strong relations with each other as either positive or negative and coefficient of correlations is higher than >60 (Fig 5). Therefore, high correlation coefficients is an indication of high performance of the model in predicting soil properties.

While Table 3 and Figure 6 shows PCR results for soil properties related to soil attributes, Table 4 and Figure 7 shows PLSR results of soil properties. Both models' result shows that they have the highest accuracy of the model and low RMSE for model predictions. This is because all predicted soils ranged from clayey to loamy texture except for Baharlı series (sandy).

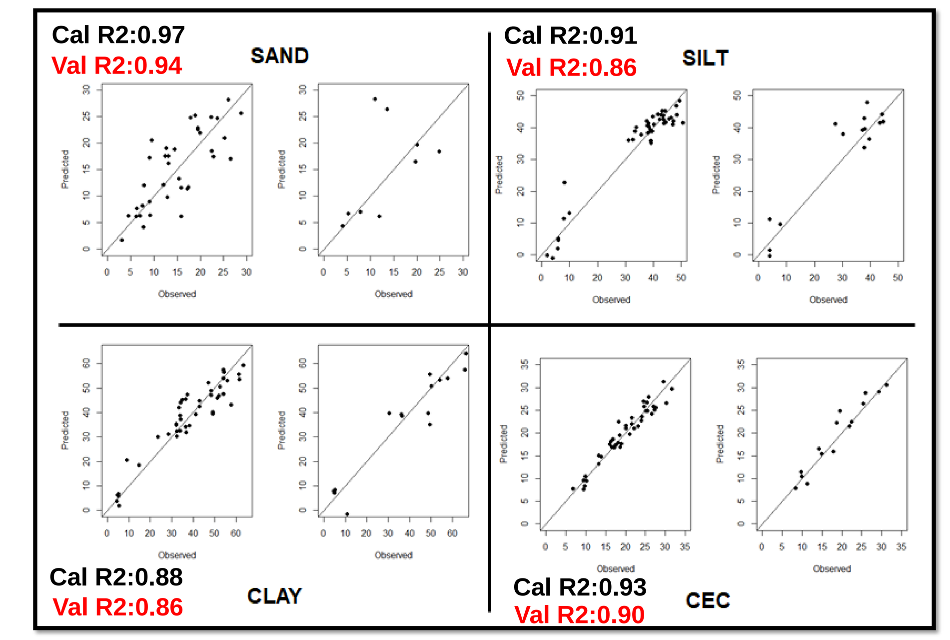

Fig 6. Observed and predicted graphics of PCR to relevant soil properties

Table 3. Prediction performance of PCR model and prediction errors of soil properties

PCR (Principle Component Regression)				
Soil Properties	LCCC	RPD	RPIQ	RMSEP
Sand	0.97	4.06	5.00	8.74
Silt	0.94	2.79	3.82	5.68
Clay	0.95	3.29	4.69	6.72
CEC	0.95	3.33	5.11	2.19

LCCC: Lin's concordance correlation coefficient, **RPD:** Relative percent Difference, **RPIQ:** Ratio of performance to interquartile distance, **RMSEP:** Root mean square error of prediction

Table 4. Prediction performance of PLSR model and prediction errors of soil properties

PLSR (Partial Least Square Regression)				
Soil Properties	LCCC	RPD	RPIQ	RMSEP
Sand	0.97	3.94	4.85	9.00
Silt	0.94	2.79	3.82	5.69
Clay	0.95	3.29	4.69	6.71
CEC	0.94	2.71	4.15	2.69

LCCC: Lin's concordance correlation coefficient, **RPD:** Relative percent Difference, **RPIQ:** Ratio of performance to interquartile distance, **RMSEP:** Root mean square error of prediction

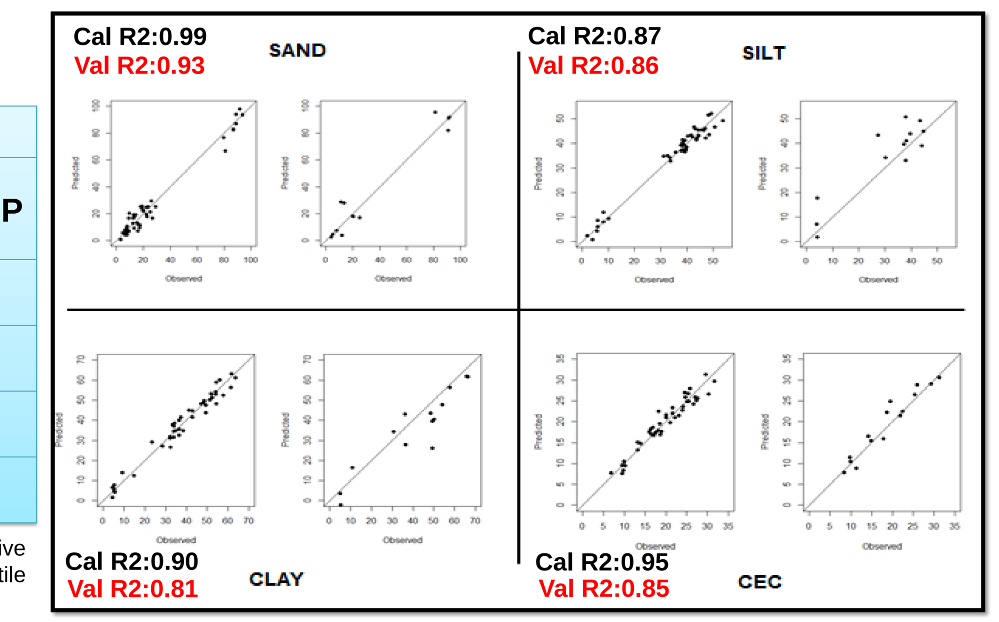

Fig 7. Observed and predicted graphics of PLSR to relevant soil properties

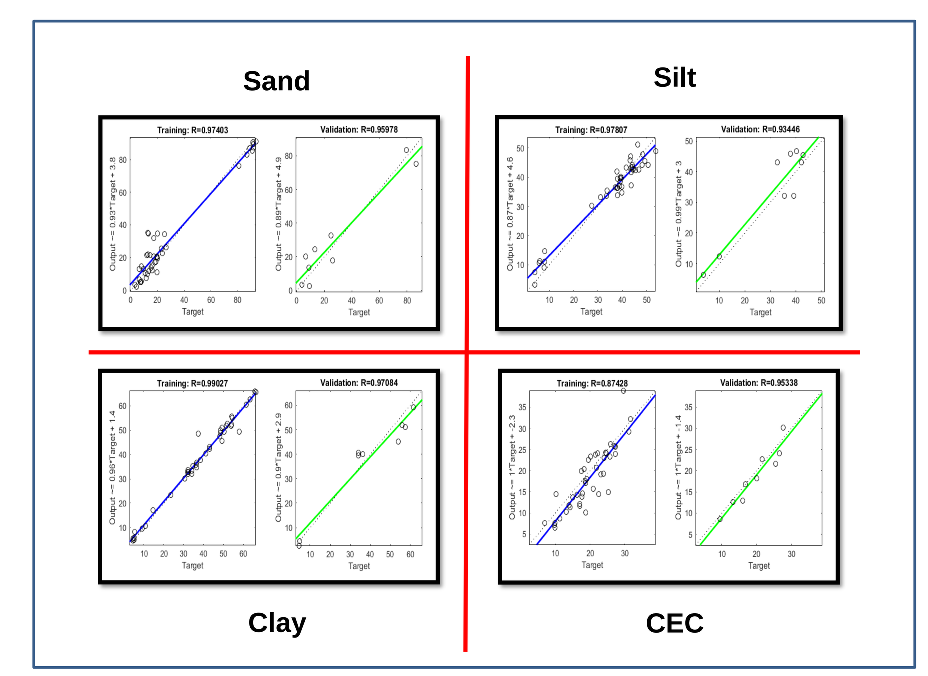

Fig 8. Result of neural network for sand, silt, clay and CEC

Table 5. Performance of the neural network of the various soil properties

Soil Properties	Calibration	Validation	RMSE
Sand	0.97	0.95	8.64
Clay	0.99	0.97	5.08
Silt	0.97	0.93	5.70
CEC	0.87	0.95	2.16

The neural network displayed great ability in the estimation of the various soil properties. Validation and the calibration both had excellent R^2 value for all the soil properties used in the neural network. Clay had the highest R^2 values in comparison to the other soil properties while CEC had the least value especially for the calibration results. However in terms of the RMSE CEC had the lowest value indicating that it has the least difference between the trained data set and the data set used in validation. Sand had the highest RMSE while clay and silt both similar values.

4.Conclusions

All of tested methods excellently predict the relevant soil properties with negligible differences. The prediction performances of the PCR model gave the highest accurate performance, PLSR model was slightly less accurate and had a high RMSEP compared to the other models but it is still reliable. The neural network displayed great ability in the estimation of the various soil properties. In terms of the selected soil properties, soils having textural differences were successfully predicted through the prediction of the model, even with limited number of samples. As a result, further studies should focus on the measurement tools and calibration of the models so that accurate prediction of site-specific soil properties changing on a narrow range can be carried out.

5.Bibliography

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