

DOI: [10.22620/agrisci.2024.43.016](https://doi.org/10.22620/agrisci.2024.43.016)

ESTIMATING SOIL SALINITY LEVEL BY PEDOTRANSFER FUNCTIONS

Coşkun GÜLSER

Ondokuz Mayıs University, Türkiye

Email: cgulser@omu.edu.tr

Abstract

In this study, the electrical conductivity (EC) of cultivated fields were predicted by pedotransfer functions (PTFs) using basic soil properties as variables in stepwise analyses. Before using PTFs, 207 soil samples were divided into development and validation datasets. This division was done 10 times to assess the accuracy and reliability of the PTFs. According to the principal component analysis (PCA), the EC values had higher load in PC1 and PC2 with clay, exchangeable Na, Ca, Mg and K contents. The EC values had significant positive correlations with pH, clay, exchangeable Ca, Mg, K, Na content, and negative correlations with silt and sand content. According to the stepwise analyses, 10 PTFs or linear multiple regression models were obtained using development data sets. The accuracy in development data sets and reliability in the validation data sets for these PTF models were assessed with R^2 and RMSE values. The higher mean R^2 and the lower mean RMSE values were obtained in the development data set when compared to the validation data set. The PTF-7 including clay, exchangeable Na, Mg and Ca was suggested to predict soil EC values of cultivated fields. It was determined that clay and exchangeable Na, Mg and Ca content were the most effective soil properties on predicting the EC values of cultivated fields.

Keywords: Salt, EC, exchangeable cations, soil texture

INTRODUCTION

Concentration of cation and anion forms of soluble minerals in soil is defined as soil salinity which is one of the most important factors affecting soil fertility and crop productivity (Pitman & Läuchli, 2002). Electrical conductivity (EC) is an indicator of the concentration of dissolved cations or anions in the bulk soil suspension (U.S. Salinity Laboratory Staff, 1954) and defines the salinity level of the soil. Friedman (2005) reported that there are three grouped factors that influenced the effective EC of the soil. The first one is related to the bulk soil and defines the aggregation, porosity, water content and structure. The second one is related to the particle shape and orientation, texture, cation exchange capacity, and wettability. The third one is environmental factors such as ionic

strength, cation composition, and temperature. In a study about using modern techniques for predicting and monitoring soil salinity in different regions of the world Gorji et al. (2015) indicated that the prediction of soil salinity is one of the main concerns to take protective measures against soil degradation. Abedi et al. (2021) applied six machine learning algorithms to model surface soil EC and Na adsorption ratio in order to explain the origin and the spatial distribution of salinity in the soil samples taken from the Darab Plain-Fars Province. Wang et al. (2018) studied various regression models for estimating soil salt content based on the spectral data for monitoring soil salt content in the Ebinur Lake Wetland National Nature Reserve, Northwest China.

The pedotransfer functions convert the direct data of soil measurement into known and unknown soil properties. They are used also for

modelling and simulations in soil research, hydrology, environmental science, assessment of climate change impact, including investigating the carbon cycle and the exchange of carbon between soils and the atmosphere to support carbon farming. In particular, the pedotransfer functions can provide the input parameters for landscape design, soil quality assessment and economic optimisation. The variables used in the pedotransfer functions, in general, are some soil properties such as clay, silt, sand, organic matter content, exchangeable cations, total porosity, and bulk density (Gülser, 2004; Gülser & Candemir, 2008; Candemir & Gülser, 2012; Gülser & Candemir, 2014; Gülser, 2016). Benke et al. (2020) derived the pedotransfer functions using a machine learning method to predict soil electrical conductivity for different locations of Victoria State in Australia. They found that the most frequently occurring predictors for EC in the pedotransfer models were soil depth, soil reaction, soil texture and geomorphological mapping unit. Mualem & Friedman (1991) used a conceptual model to predict electrical conductivity of saturated and unsaturated bulk soils. They reported that electrical conductivity of the bulk soil was predicted as a function of soil water content and soil hydraulic conductivity and the utilization of limited number of soil samples was, in general, a good estimation for electrical conductivity. Lake et al. (2009) developed the pedotransfer functions to predict soil physico-chemical and hydrological properties in the Southern coastal zones of the Caspian Sea. They concluded that predicting the soil properties by means of PTFs, the input data were consisted of the concentration of soluble Na and Cl for EC, and the RMSE of the model was 240 dS/m. Andrade Foronda & Colinet (2023) studied on machine learning algorithms to predict soil exchangeable Na percentage (ESP), EC from the soluble salt ions (Na^+ , K^+ , Ca^{2+} , Mg^{2+} , HCO_3^- , Cl^- , CO_3^{2-} , SO_4^{2-}) as major variables. They concluded that the content of soluble Na^+ was the most relevant variable for all predictions, followed by Ca^{2+} ,

Mg^{2+} , Cl^- , and HCO_3^- . Mondal et al. (2001) developed multiple linear and non-linear regression models to predict the surface soil EC of the fallow land for both moderately and saline soils by using daily rainfall and evaporation as independent variables. They concluded that the prediction level was not significantly improved when a non-linear model was employed in place of linear model to predict soil salinity of the coastal rice lands of Bangladesh. Shrestha (2006) studied the relationship between physico-chemical soil properties and electrical conductivity (EC) of soil samples in northeast Thailand using multiple regression models. The researcher found that the observed EC values of the surface soils correlated mostly with chloride (Cl), sodium (Na), phosphorus (P), and sodium adsorption ratio (SAR), and Cl and P found to be significant predictors of EC values.

The objective of the study was to derive the pedotransfer functions in order to predict the soil EC values using basic soil properties in cultivated cropland fields.

MATERIALS AND METHODS

In this study, the relationships between soil electrical conductivity (EC) and some soil physicochemical properties were determined in 207 surface soil samples (0-20 cm) taken from cropland fields around Bafra and Carsamba Plains of Samsun, Türkiye. Some basic soil properties were analyzed as follows: particle size (clay - C, silt - Si and sand - S) and distribution by hydrometer method (Demiralay, 1993), soil reaction (pH) (w:v, 1:1, soil:water suspension) and electrical conductivity ($\text{EC}_{25^\circ\text{C}}$) in the same soil suspension was measured by pH meter and EC meter, respectively (Rowell, 1994). Organic matter (OM) content was determined using the modified Walkley-Black method, and exchangeable cations (Ca, Mg, Na, K) by ammonia acetate extraction method (Kacar, 1994).

To predict the EC values of soil samples, a linear multiple regression equation between

EC and the soil properties was obtained using the stepwise analyses with SPSS program. Principle component analysis (PCA) was also applied as a predictor extraction algorithm for reducing the dimensionality of data set (Hegde & Vidyapeetham, 2016).

The accuracy and reliability of the PTFs were assessed by cross-validation using the development and validation. The random splitting of data set was repeated ten times. For the accuracy and reliability analyses of the PTFs, the root mean square error (RMSE) in Eq.1 and the relative error (RE) in Eq.2 of PTFs were calculated for each development and validation data set (Pachepsky & Rawls, 1999).

$$RMSE = \left[\frac{1}{n} \sum_{i=1}^n (y_i - y_i')^2 \right]^{1/2} \quad (1)$$

$$RE = \left[\frac{1}{n} \sum_{i=1}^n \frac{(y_i' - y_i)}{y_i} \right] \cdot 100\% \quad (2)$$

Where, y_i and y_i' represent the measured and computed EC values, respectively, and n represents the number of data.

RESULTS AND DISCUSSION

Descriptive statistics for some physical and chemical properties of the soil samples used

in the study are given in Table 1. The soil samples values generally showed a normal distribution for most of the soil properties, except EC, pH and exchangeable Na content. Particle size distribution of the samples was classified as 40% fine, 32% moderate and 28% coarse textural soil. According to the EC values, 87.9% of soil samples were none saline, 9.2% were very slightly saline and 2.9% were slightly saline. Distribution of soil reaction (pH) level of samples was classified as 1.2% very strongly acid, 7.6% slightly acid, 21.7% neutral, 39.6% slightly alkaline and 29.9% moderately alkaline. Organic matter contents of samples were 12.1% very low, 46.3% low, 33.3% moderate and 8.3% high (Soil Survey Staff, 1993). A lower coefficient of variation (CV) value showed the homogeneity of samples and the accuracy of experiment (Ogunkunle & Eghaghara, 2007). In this study, while exchangeable Na and EC values of the samples had higher coefficient of variation (CV), soil reaction (pH) had the lowest CV among the soil properties of cultivated fields. Similarly, Gülser et al. (2021) reported that exchangeable Na content generally had the highest CV in different soil types while the soil pH had the lowest CV.

Table 1. Descriptive statistics of some soil properties (n=207).

	Minimum	Maximum	Mean	Std. Deviation	CV, %	Skewness	Kurtosis
EC, $\mu\text{S/cm}$	110.00	2949.00	659.56	425.56	64.5	2.73	10.59
C, %	9.99	68.73	35.42	13.89	39.2	0.20	-0.62
Si, %	3.05	66.37	28.53	8.94	31.3	0.55	0.82
S, %	4.27	81.71	36.04	16.35	45.4	0.56	-0.48
OM, %	0.20	4.19	1.97	0.75	38.1	0.29	-0.19
pH (1:1)	4.85	8.33	7.51	0.60	7.9	-1.76	3.43
Ca, cmol/kg	2.36	52.53	21.73	9.76	44.9	0.01	-0.48
Mg, cmol/kg	0.52	21.12	7.05	4.40	62.4	0.69	-0.05
K, cmol/kg	0.11	1.79	0.58	0.33	56.9	0.98	0.71
Na, cmol/kg	0.08	5.64	0.62	0.75	120.9	4.03	21.37

Legend: EC: Electrical Conductivity, C: Clay, Si: Silt, S: Sand, OM: organic matter, CV: Coefficient of variation

The correlation matrix between EC values and some soil properties is given in Table 2. Silt and sand contents showed negative correlations with EC while exchangeable cations (Ca, Mg, K, Na), pH and clay content had significant correlations with EC values. The correlation values between EC and exchangeable cations were ordered as follows: Ca (0.266**) < K (0.332**) < Mg (0.514**) < Na (0.800**). The highest significant correlation was found between EC and exchangeable Na content (Figure 1). Similarly, the high correlation between EC and exchangeable Na was indicated in other studies - Lake et al. (2009) – 0.4** and Taghizadeh

Mehrjardi et al. (2008) – 0.80**. Rodriguez Perez et al. (2011) reported that apparent soil EC had significant correlations with exchangeable Na and Mg due to strong association of these cations with EC of the soil while the correlations between EC and other exchangeable cations (Ca and K) were not significant. In another study by Shrestha (2006), EC values of soil samples in northeast Thailand have significant correlation with Na (0.82), Mg (0.55) and Ca (0.27). When comparing with the other studies, EC values in this study also showed significant positive correlations with Na, Mg and Ca in the same order.

Table 2. The correlation matrix of EC values and soil properties.

	C	Si	S	pH	OM	Ca	Mg	K	Na
EC	0.404**	-0.010	-0.337**	0.250**	0.124	0.266**	0.514**	0.332**	0.800**
C		-0.022	-0.837**	0.269**	0.566**	0.514**	0.404**	0.513**	0.190**
Si			-0.529**	0.170*	0.079	0.001	0.011	-0.085	-0.005
S				-0.321**	-0.524**	-0.437**	-0.349**	-0.389**	-0.159*
pH					0.119	0.585**	0.490**	0.243**	0.181**
OM						0.413**	0.302**	0.440**	-0.060
Ca							0.543**	0.524**	0.033
Mg								0.481**	0.402**
K									0.159*

Legend: ** Correlation is significant at the 0.01 level, * Correlation is significant at the 0.05 level.

Exploratory factor analysis of the nine soil properties was conducted using principal component analysis (Table 3). EC had higher positive loading in the first two components (PC1 and PC2). The eigenvalues of the first 4 PC factors were greater than 1 and explained 81.65% of the variation of soil properties. The PC1 explained 40.82% of the variation, and had high positive loadings from C (0.810), Mg (0.739), Ca (0.738), K (0.687), and EC (0.629). The PC2 explained 57.73% of the variation, and had high positive loadings from Na (0.803) and EC (0.656). Clay content had significant positive correlations with exchangeable cations (Ca, Mg, K and Na), EC and pH values of the soil samples (Table 2, Figure 1). According to PC1 and PC2 results, exchangeable cations and clay content were selected as the proper

variables in the PTFs to predict salinity or EC values of the soil samples.

After repeated random splitting of the data set into 10 different subsets for development and validation tests, the PTF models obtained using the development data set by stepwise analysis are given in Table 4. In the PTF models, only five soil properties (C, Na, Mg, Ca and K) out of 9 were selected to give the best prediction of soil EC in each developing data set by stepwise analysis. According to the selected variables in the PTFs, two groups of variables, which were C, Na and Ca in the first group and C, Na and Mg in the second group, were used in the PTF models more than once. The first group variables were used in number 1, 2, 3, 4 and 10 PTFs while the second group variables were used in number 6, 8 and 9 PTFs. Exchangeable K content besides Na and Ca

were only used in number 5 PTF model and C, Na, Mg and Ca together were only used in number 7 PTF model (Table 4).

The determination coefficient (R^2) and RMSE values were also determined for development and validation data sets (Table 4). The descriptive statistics for R^2 , RMSE values and relative error (RE) of validation set are also given in Table 4. The accuracy of PTFs was assessed by the RMSE of the development data set, whereas the reliability of PTFs was assessed by the RMSE of the validation data set. The RMSE values for development data sets varied between 184.84 $\mu\text{S/cm}$ and 240.43 $\mu\text{S/cm}$ with the mean of 221.57 $\mu\text{S/cm}$ while the RMSE values for the validation data sets varied between 180.29 $\mu\text{S/cm}$ and 319.14 $\mu\text{S/cm}$ with the mean of 238.43 $\mu\text{S/cm}$. Fu et al. (2021) developed a model to estimate bulk soil EC with RMSE values ranging from 8 $\mu\text{S/cm}$ to 399 $\mu\text{S/cm}$ and relative errors ranging from 0.7% to 29.8%. In another study, Benke et al. (2020) developed PTFs to predict the soil EC by machine learning method and found the prediction error for the top ranked model as 686

$\mu\text{S/cm}$ MSE or 828 $\mu\text{S/cm}$ RMSE. The highest determination coefficient (R^2) for developing and validation data sets were determined in number 2 (0.796**) and number 8 (0.867**) PTF models, respectively (Table 4). The lowest relative error (7.82%) was found in number 4 PTF model.

Table 3. Component matrix after rotating by maximum variance

Component Matrix				
	PC1	PC2	PC3	PC4
EC	0.629	0.656	-0.152	-0.202
C	0.810	-0.222	0.045	-0.346
Si	0.155	-0.315	-0.865	0.185
S	-0.772	0.361	0.435	0.192
OM	0.593	-0.472	0.152	-0.320
pH	0.569	0.045	-0.047	0.717
Na	0.415	0.803	-0.251	-0.177
K	0.687	-0.067	0.373	-0.119
Ca	0.738	-0.186	0.292	0.381
Mg	0.739	0.269	0.132	0.246
Eigenvalue	4.082	1.691	1.294	1.099
Cumulative var. contribution rate, %	40.82	57.73	70.67	81.65

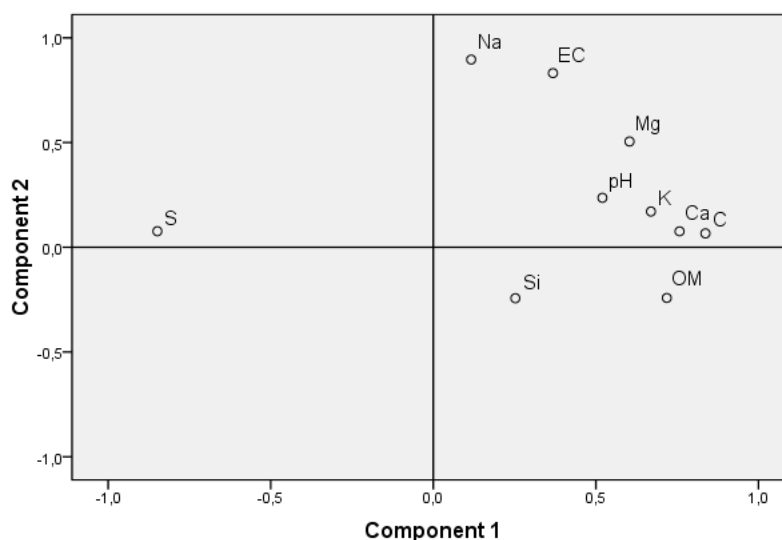


Figure 1. Component plot in rotated space for the soil properties

There were significant negative correlations between R^2 (-0.910**) and between RMSE (-0.984**) values for the EC estimates in development and validation data sets. However, Pachepsky et al. (1999) reported that

there was not dependence between RMSE values for the estimate soil moisture constant in development and validation data sets and R^2 values had positive dependence in development and validation data sets. The negative

correlations for R^2 and RMSE between development and validation data sets can be explained with non-normal distribution of EC values in the soil samples. The coefficient of

variation values of R^2 (6.29%) and RMSE (9.29%) determined in the development data set were lower than that R^2 (21.13%) and RMSE (21.44%) determined in the validation data set.

Table 4. The PTF models developed to predict EC values in cultivated soils

No	PTF Models	R^2 develop.	R^2 valid.	RMSE develop. $\mu\text{S/cm}$	RMSE valid. $\mu\text{S/cm}$	RE valid. %
1	EC=68,86+430,59 Na+5,48 C+5,69 Ca	0.758	0.660	184.84	319.14	14.79
2	EC=96,66+436,46 Na+4,76 C+5,83 Ca	0.796	0.444	195.60	302.33	22.64
3	EC=63,80+426,52 Na+4,73 C+7,72 Ca	0.665	0.847	236.89	190.85	15.35
4	EC=114,16+412,75 Na+4,47 C+5,19 Ca	0.757	0.695	198.20	302.94	7.82
5	EC=109,18+438,47 Na+9,18 Ca+137,66 K	0.686	0.759	235.81	220.46	19.01
6	EC=61,66+400,92 Na+6,70 C+17,29 Mg	0.765	0.459	224.88	233.76	13.97
7	EC=50,00+410,51 Na+4,78 C+3,97 Ca+14,78 Mg	0.700	0.801	236.36	202.73	8.82
8	EC=125,97+410,48 Na+5,47 C+13,70 Mg	0.661	0.867	240.43	180.29	23.40
9	EC=65,30+384,75 Na+5,91 C+22,03 Mg	0.737	0.648	227.29	231.69	16.75
10	EC=64,41+442,48 Na+4,21 C+8,25 Ca	0.729	0.686	235.42	199.13	13.84
	Minimum	0.665	0.444	184.84	180.29	7.82
	Maximum	0.796	0.867	240.43	319.14	23.40
	Mean	0.725	0.686	221.57	238.43	15.64
	Standard Deviation	0.046	0.145	20.59	51.14	5.11
	Coefficient of Variation, %	6.29	21.13	9.29	21.44	32.70

In this study, the PTF model 7 including C, Na, Mg and Ca variables can be suggested to predict the EC values due to having lower RMSE and higher R^2 values for both development and validation data sets and a lower relative error (8.82%) compare with the

other PTFs (Figure 2). Also, the PTF model 8, having the highest R^2 and the lowest RMSE values for validation data set, can be suggested to predict the soil EC values of cultivated fields (Figure 3).

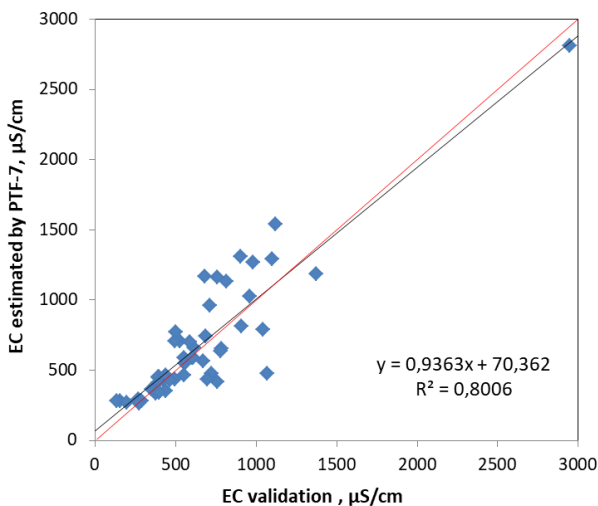


Figure 2. Relationship between EC values of validation data set and EC values estimated by PTF model 7.

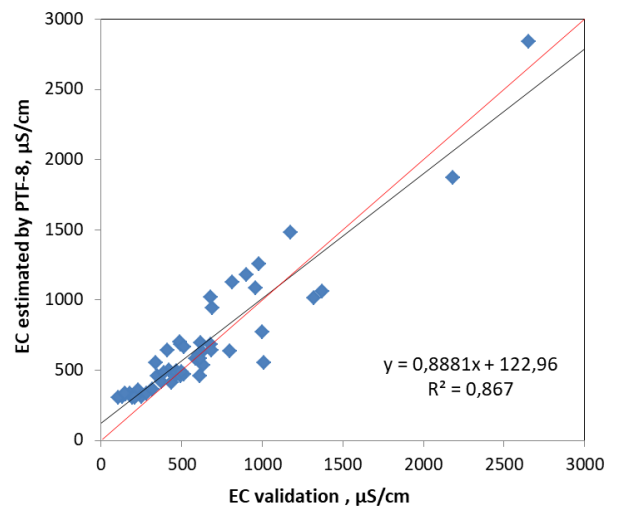


Figure 3. Relationship between EC values of validation data set and EC values estimated by PTF model 8.

CONCLUSION

Soil salinity is one of the most important soil parameters and helps for explaining many soil physical, chemical and biological processes. Soil salinity level, generally, is calculated using the EC value of soil solution. In this study, the EC values were predicted by PTFs based on basic soil properties of 207 soil samples of cultivated fields. Before developing PTFs to predict soil EC values, soil samples were divided for developing (3/4) and validation data (1/4) sets 10 times to explain accuracy and reliability of PTFs, respectively. According to the PC analyses result, EC values had higher load in PC1 and PC2 with clay, exchangeable Na, Ca, Mg and K contents. EC values had also significant positive correlations with these soil properties. According to the stepwise analyses, ten PTFs or linear multiple regression models were produced and accuracy and reliability of these models were assessed with determination coefficients (R^2) and RMSE values. The higher average R^2 and lower average RMSE were determined in developing data set compared to validation data set. The PTF-8 including clay, exchangeable Na, Mg and Ca variables and having almost higher R^2 and lower RMSE and RE can be suggested to predict soil EC values of cultivated fields.

REFERENCES

- Abedi, F., Amirian-Chakan, A., Faraji, M., Taghizadeh-Mehrjardi, R., Kerry, R., Razmjoue, D. & Scholten, T. (2021). Salt dome related soil salinity in southern Iran: Prediction and mapping with averaging machine learning models. *Land Degradation & Development*, 32(3), 1540-1554.
- Andrade Foronda, D., & Colinet, G. (2023). Prediction of soil salinity/sodicity and salt-affected soil classes from soluble salt ions using machine learning algorithms. *Soil Systems*, 7(2), 47.
- Benke, K. K., Norng, S., Robinson, N.J., Chia, K., Rees, D.B. & Hopley, J. (2020). Development of pedotransfer functions by machine learning for prediction of soil electrical conductivity and organic carbon content. *Geoderma*, 366, 114210.
- Candemir, F., & Gülser, C. (2012). Influencing Factors and Prediction of Hydraulic Conductivity in Fine Textured-Alkaline Soils. *Arid Land Research Management*, 26, 15-31.
- Demiralay, İ. (1993). Toprak fiziksel analiz yöntemleri. Atatürk Üniversitesi Ziraat Fakültesi yayınları. Erzurum, 111-120.
- Friedman, S. P. (2005). Soil properties influencing apparent electrical conductivity: a review. *Computers and electronics in agriculture*, 46(1-3), 45-70.
- Fu, Y., Horton, R., Ren, T., & Heitman, J.L. (2021). A general form of Archie's model for estimating bulk soil electrical conductivity. *Journal of Hydrology*, 597, 126160.
- Gorji, T., Tanik, A., & Sertel, E. (2015). Soil salinity prediction, monitoring and mapping using modern technologies. *Procedia Earth and Planetary Science*, 15, 507-512.
- Gülser C., & Candemir, F. (2014). Using soil moisture constants and physical properties to predict saturated hydraulic conductivity. *Eurasian Journal of Soil Science*, 3(1), 77 – 81.
- Gülser, C. (2016). Predicting aggregate stability of cultivated fields using soil properties. "Spatial Data Processing, Modelling, Analysing and Management for Knowledge Based Systems". International Scientific Conference on Applied Sciences, 27-30 September 2016 - Antalya/Türkiye.
- Gülser, C. (2004). Tarla kapasitesi ve devamlı solma noktasının toprakların fiziksel ve kimyasal özellikleri ile ilişkili pedotransfer eşitliklerle belirlenmesi.

- Ondokuz Mayıs Üniversitesi Ziraat Fakültesi Dergisi (Anadolu Tarım Bilimleri Dergisi), 19(3), 19-23.
- Gülser, C., Ekberli, İ., & Gülser, F. (2021). Effects of deforestation on soil properties and organic carbon stock of a hillslope position land in Black Sea Region of Turkey. *Eurasian Journal of Soil Science*, 10(4), 278-284.
- Gülser, C., & Candemir, F. (2008). Prediction of Saturated Hydraulic Conductivity Using Some Moisture Constants and Soil Physical Properties. BALWOIS, Ohrid, Republic of Macedonia, 27-31, May. P.328.
- Hegde, V., & Vidyapeetham, A.V. (2016). A comparative study of principal component analysis vs wrapper method, an overview of dimensionality reduction techniques applied in developing an undergraduate student dropout model. *International Journal of Control Theory and Applications*, 9(42), 45–55.
- Kacar, B. (1994). Bitki ve toprağın kimyasal analizleri:III. Ankara Üniversitesi Ziraat Fakültesi Eğitim, Araştırma ve Geliştirme Vakfı Yayınları, 3, 89-98.
- Lake, H. R., Akbarzadeh, A., & Mehrjardi, R. T. (2009). Development of pedotransfer functions (PTFs) to predict soil physico-chemical and hydrological characteristics in southern coastal zones of the Caspian Sea. *Journal of Ecology and the Natural Environment*, 1(7), 160-172.
- Mondal, M. K., Bhuiyan, S. I., & Franco, D. T. (2001). Soil salinity reduction and prediction of salt dynamics in the coastal ricelands of Bangladesh. *Agricultural water management*, 47(1), 9-23.
- Mualem, Y., & Friedman, S.P. (1991). Theoretical prediction of electrical conductivity in saturated and unsaturated soil. *Water Resources Research*, 27(10), 2771-2777.
- Ogunkunle, A.O., & Eghaghara, O. O. (2007). Influence of land use on soil properties in a forest region of Southern Nigeria. *Soil Use and Management*, 8(3), 121–124.
- Pachepsky, Y. A., & Rawls, W. J. (1999). Accuracy and reliability of pedotransfer functions as affected by grouping soils. *Soil Science Society of America Journal*, 63(6), 1748-1757.
- Pitman, M. G., & Läuchli, A. (2002). Global impact of salinity and agricultural ecosystems. *Salinity: environment-plants-molecules*, 3, 20.
- Rodríguez-Pérez, J. R., Plant, R. E., Lambert, J. J., & Smart, D. R. (2011). Using apparent soil electrical conductivity (EC a) to characterize vineyard soils of high clay content. *Precision Agriculture*, 12, 775-794.
- Rowell, D. L. (1994). *Soil science: Methods & applications*. Longman, UK.
- Shrestha, R. P. (2006). Relating soil electrical conductivity to remote sensing and other soil properties for assessing soil salinity in northeast Thailand. *Land degradation & development*, 17 (6), 677-689.
- Soil Survey Staff, (1993). *Soil Survey Manual*. USDA Handbook No:18 Washington.
- US Salinity Laboratory Staff, (1954). *Diagnosis and improvement of saline and alkali soils*. Agriculture handbook, 60, 83-100.
- Taghizadeh Mehrjardi, A, Akbarzadeh A, Mahmoodi S., Heidari, A., & Sarmadian, F. (2008). Application of geostastical methods for mapping groundwater quality in Azarbayjan province, Iran. *American-Eurasian J. Agric. Environ. Sci.*, 3(5), 726-735.
- Wang, X., Zhang, F., Ding, J., Latif, A. & Johnson, V.C. (2018). Estimation of soil salt content (SSC) in the Ebinur Lake Wetland National Nature Reserve (ELWNNR), Northwest China, based on a Bootstrap-BP neural network model and optimal spectral indices. *Science of the Total Environment*, 615, 918-930.