Interpolation Approaches for Characterizing Spatial Variability of Soil Properties in Tuz Lake Basin of Turkey

Taha Gorji¹, Elif Sertel², Aysegul Tanik³

1 Istanbul Technical University (ITU), Informatics Institute, 34469, Maslak-Istanbul, Turkey
2 Istanbul Technical University (ITU), Faculty of Civil Engineering, Department of Geomatics Engineering, 34469, Maslak-Istanbul, Turkey
3 Istanbul Technical University (ITU), Faculty of Civil Engineering, Department of Environmental Engineering 34469, Maslak-Istanbul, Turkey

sertele@itu.edu.tr

Abstract. Soil management is an essential concern in protecting soil properties, in enhancing appropriate soil quality for plant growth and agricultural productivity, and in preventing soil erosion. Soil scientists and decision makers require accurate and well-distributed spatially continuous soil data across a region for risk assessment and for effectively monitoring and managing soils. Recently, spatial interpolation approaches have been utilized in various disciplines including soil sciences for analysing, predicting and mapping distribution and surface modelling of environmental factors such as soil properties. The study area selected in this research is Tuz Lake Basin in Turkey bearing ecological and economic importance. Fertile soil plays a significant role in agricultural activities, which is one of the main industries having great impact on economy of the region. Loss of trees and bushes due to intense agricultural activities in some parts of the basin lead to soil erosion. Besides, soil salinization due to both human-induced activities and natural factors has exacerbated its condition regarding agricultural land development. This study aims to compare capability of Local Polynomial Interpolation (LPI) and Radial Basis Functions (RBF) as two interpolation methods for mapping spatial pattern of soil properties including organic matter, phosphorus, lime and boron. Both LPI and RBF methods demonstrated promising results for predicting lime, organic matter, phosphorous and boron. Soil samples collected in the field were used for interpolation analysis in which approximately 80% of data was used for interpolation modelling whereas the remaining for validation of the predicted results. Relationship between validation points and their corresponding estimated values in the same location is examined by conducting linear regression analysis. Eight prediction maps generated from two different interpolation methods for soil organic matter, phosphorus, lime and boron parameters were examined based on R² and RMSE values. The outcomes indicate that RBF performance in predicting lime, organic matter and boron put forth better results than LPI. However, LPI shows better results for predicting phosphorus.

1. Introduction
Monitoring soil properties by applying conventional chemical methods is always expensive and requires time, manpower and budget especially when large regions are concerned, [1],[2]. Modern mapping and interpolation methods are addressed as new and advanced techniques [3], [4] that attain soil information through estimating spatial variation of soil characteristics based on field measurements, environmental
information and application of various spatial interpolation methods [5]. Utilizing advanced interpolation methods give rise to better understand spatial and temporal changes of soil properties. In addition, these methods minimize cost and time required for soil sampling [6]. As such, interpolation methods attracted the interest of decision makers due to their beneficial and low cost prediction of un-sampled locations within the last two decades [7][8][9][10].

Providing accurate and continuous spatial data can remarkably be supportive for decision making in environmental management [11]. Limitation in field measurements and existence of usually a nonlinear relationship between geographical variables and soil properties are the two main factors that adversely affect surface modelling of soil properties [12]. Besides, land use, soil type and parent material can be accounted as the other significant handicaps on determining spatial variation of soil properties [5]. Geo-statistics support collection of statistical tools for spatial interpolation. These methods bring about not only prediction surfaces; but also error or uncertainty surfaces [13].

Numerous spatial interpolation approaches are utilized to predict the values at unmeasured locations from the surface generated by measured sampling points [14]. There are several factors like sampling strategy, sample size and data properties that affect the performance of interpolation methods [15]. There is no comprehensive interpolation algorithm which can be used for each study area. Capability of each prediction and interpolation approach is based on the spatial pattern and soil characteristics correlation in every location [11].

Many interpolation methods may be tested to select the appropriate interpolation approach for an area [16]. A few of the recent studies may be mentioned accordingly. In India, scientists used five various interpolation methods including local polynomial interpolation (LPI), radial basis function (RBF) inverse distance weighting (IDW), ordinary kriging (OK) and Empirical Bayes kriging (EBK) in order to map soil organic carbon (SOC) pattern where RBF and LPI showed satisfactory results in predicting SOC in soil depth of 0 - 20 cm with $R^2$ value of 0.74 and 0.79, respectively [17]. In another study, researchers have compared performance of interpolation methods for estimating spatial distribution of top soil pH and EC in Hamadan Province, Western Iran. The result demonstrated high performance of spatial estimation of inverse distance weighting (IDW) and radius basis function (RBF) methods [16]. In Buyukcekmece Basin located in Istanbul- Turkey, scientists analysed various interpolation approaches including Global Polynomial Interpolation (GPI), Local Polynomial Interpolation (LPI), Radial Basis Functions (RBF), Inverse Distance Weighting (IDW), Kriging and Cokriging for predicting soil moisture content. The results indicated accurate and proper estimation with nearly similar results for all approaches [18]. A different study was conducted for predicting spatial distribution of heavy metals such as cadmium, copper and lead in the mid Tongzhou district, Beijing- China by applying various interpolation methods including local polynomial (LPI), ordinary kriging (OK), radial basis functions (RBF) and inverse distance weighting (IDW). The results showed that all the interpolation methods have an impact on the pollution area prediction, but OK and RBF interpolations have the minimum root mean square error (RMSE) [19]. Another case study conducted in Sirppujoki River catchment, south western Finland, demonstrated how artificial neural network (ANN) based on a RBF was utilized effectively for estimating sulphur and organic matter content in soil. RBF-based ANN method displayed promising and accurate estimation of soil organic matter and sulphur content in the region [20]. Near Vilnius in Lithuania, scientists tested several geo-statistical and interpolation methods including Ordinary Kriging (OK), Simple Kriging (SK), Inverse Distance Weighting (IDW) with the power of 1, 2, 3, 4 and 5, Local Polynomial (LP) with the power of 1 (LP1) and 2 (LP2), Spline with Tension (SPT), completely regularized spline (CRS), multiquadratic (MTQ), inverse multiquadratic (IMQ) and Thin Plate Spline (TPS) for monitoring the spatio-temporal evolution of ashes in soil after a fire. The results demonstrated that LP1 method with the lowest RMSE of 4.3 was the most precise and promising technique for interpolating the ash thickness in the soil [21]. One other study performed in south of Heraklion city in the island of Crete, Greece, indicated capability of Ordinary Kriging (OK), Inverse Distance Weighting (IDW), and Radial Basis Functions (RBF) methods for mapping and estimating soil properties including organic matter, total CaCO$_3$, electrical conductivity (EC), Fe content, and clay content. The suitability of prediction is calculated for various methods and it showed positive values only for total CaCO$_3$ and Fe
content for all the interpolation approaches, and marginally positive values were attained only for organic matter utilizing IDW. In addition, electrical conductivity (EC) and clay content proved negative values for all the examined interpolation methods [22].

This study aims to compare the performance of Local Polynomial Interpolation (LPI) and Radial Basis Functions (RBF) as two different interpolation approaches for mapping spatial variation of soil characteristics including soil organic matter, phosphorus, lime and boron in the Tuz Lake Basin of Turkey by using soil samples collected in the field.

2. Materials and Method

2.1. Study Area
Tuz Lake Basin with a surface area of 1500 km$^2$ is located in the Central Anatolian Region of Turkey and is the second largest lake of the country. Parent materials in the soils of Tuz Lake have been formed mostly from the ancient lake major sediments and volcanic rocks [23]. The economic condition in the region is mainly based on agriculture, livestock breeding, salt production and tourism [24]. Soil properties tend to change by human-induced activities and natural factors in the region. Studies on land-use/cover changes using CORINE data demonstrated minor changes by anthropogenic factors between years 2000–2012 [25].

Information on soil properties is valuable in the sense of conservation, management and reclamation of the area as the region has ecological significance. It supports almost 6000 nesting and breeding areas for migrating birds and it is suitable place for halophytic plants of 279 different types. In addition, it has also economic importance in consideration of supplying salt resources in Turkey [26]. The majority of the basin has been declared as a Special Protection Area and has been temporarily registered in the World’s Heritage List of UNESCO. Therefore, this sensitive basin is selected as the study area. It is well known that soil properties form an integral part of management efforts. The geographical location of the lake is depicted coupled with a Landsat satellite image of year 2015 with a closer view in Figure 1.

![Figure 1. Geographical location of Tuz Lake Basin in Turkey](image)

2.2. Data Analysis
A total number of 312 soil samples had been collected and analyzed by the Ministry of Food, Agriculture and Livestock of Turkey within the context of a national project on soil quality and land classification
together with the determination of alternative agricultural practices of Tuz Lake Region [27]. Among all data, 50 samples that were homogeneously distributed around the lake are selected as validation samples for checking the accuracy and performance of each interpolation method; whereas, the remaining 262 samples were reserved for generating the prediction maps by utilizing two interpolation methods, namely RBF and LPI methods for organic matter, phosphorus, lime and boron.

Soil organic matter is the basis of soil fertility since it provides nutrients for plant growth and supports biological health of plant and soil. Lime is another important soil parameter which increases water penetration and as a result it makes water uptake easier for plants. Regarding to importance of phosphorus, it is known that adding this element to soil improves plant root growth and cell division. Also, providing required amount of boron in soil support plant cell wall formation [28]. Excess amounts of any of these concerned soil properties lead to degradation of soil and diminish its fertility/utility. Thus, mapping of various soil characteristics is highly important for the regional decision-makers and managers in charge of this vulnerable basin.

2.3. Local Polynomial Interpolation (LPI)
LPI is an inexact interpolation approach for commonly producing a smooth surface in short-range variation. It considers points that are inside the determined neighbourhood for fitting the local polynomial. In this deterministic method that does not produce standard errors, the interpolated surface is not considered to pass through the data [29]. In this study, LPI method is utilized in ArcMap 10.1 to generate a model for predicting location between 262 known samples. Then, a linear regression analysis is built up among the measured validation points, and their corresponding estimated values in the same location. Finally, four prediction maps for soil organic matter, phosphorus, lime and boron are produced by applying the linear regression equation for each soil parameter.

2.4. Radial Basis Function (RBF)
RBF approach is an exact interpolation technique to interpolate multi-dimensionally distributed data considering that the analyzed surface should go through each measured sample value [30]. In this research, a model is generated by applying Radial Basis Function (RBF) approach in ArcMap 10.1 for each soil property in order to estimate the value of unknown location between 262 known samples. Relationship between known measured validation points and their corresponding estimated values in the same location is examined by conducting linear regression analysis to evaluate the performance of this approach to create four prediction maps for soil organic matter, phosphorus, lime and boron parameters are produced.

3. Results and discussion
Precision of LPI and RBF interpolation methods for predicting soil organic matter, phosphorus, lime and boron are illustrated in Table 1.

In this study, Root Mean Square Error (RMSE) and R-squared ($R^2$) are used as the two common statistical measures for interpreting the performance of results. $R^2$ indicates the degree of closeness of the predicted data to the measured validation points. The closer to the $R^2$ value to 1, the higher the prediction accuracy. RMSE is utilized for measuring the error of estimation. The lowest RMSE value indicates the most accurate estimation. In this research, RBF indicates slightly better performance for estimating lime and boron compared to LPI; whereas, considerably better performance is obtained for organic matter. However, LPI illustrates remarkably better performance than RBF approach to create prediction map of phosphorus.

Range variations of each variable were analysed using semi-variograms. Results verified the capability of LPI to capture the short range variation while producing the prediction maps and indicated that phosphorus has the shortest range values compared to other investigated soil parameters.
Table 1. Precision of the interpolation methods for predicting various soil properties

| Interpolation Method | Lime  | Phosphorus | Organic matter | Boron |
|----------------------|-------|------------|----------------|-------|
|                      | R²    | RMSE       | R²             | RMSE  |
| LPI                  | 0.88  | 7.24       | 0.80           | 6.59  |
|                      | 0.66  | 0.64       | 0.72           | 5.17  |
| RBF                  | 0.90  | 7.20       | 0.73           | 7.15  |
|                      | 0.72  | 0.55       | 0.74           | 5.23  |

Prediction maps applying LPI and RBF methods for organic matter, phosphorus, lime and boron are given in Figure 2 a, b, c, d, respectively. It can be stated that LPI produces smoother maps compared to RBF method. In literature, RBF and LPI interpolation methods on estimating boron, lime and phosphorous are rarely seen; however, these methods are applied for estimating organic matter and other soil properties such as electrical conductivity (EC), pH and soil moisture in several case studies. For instance, RBF and LPI methods demonstrated promising results in predicting SOC in soil depth 0-20 cm with R² value of 0.74 and 0.79 in West Bengal, India [17]. In this research, the four soil properties exerted higher values for soil near the lake especially in the southern part as estimated in the maps. In addition, LPI method estimated higher concentration for all four-soil properties in the area compared to results of the RBF method. According to RMSE values that are shown in Table 1, RBF method produced more accurate maps for soil lime and organic matter with RMSE values of 7.2 and 0.55, respectively. However, LPI method produced more accurate map for soil phosphorous considering RMSE value of 6.59 compared to RBF method, which has higher RMSE value for predicting soil phosphorous in the region.
4. Conclusions

Spatial interpolation approaches are considerably favourable for analysing, predicting and mapping soil properties. Sample size, sampling strategy and data properties are the main factors, which affect performance and estimation of interpolation approaches. Selection and utilizing the proper interpolation method is considerably dependent to characteristics of the dataset in each case study. Therefore, there is no comprehensive method, which can be defined, and it can be conducted properly for all sorts of studies.

In this study, LPI and RBF methods demonstrated promising results for predicting soil lime, organic matter, phosphorous and boron. It can be concluded that applying such interpolation methods can be effective for finding out information about soil properties in especially large areas that would further be used to maintain and conserve soil in different land-use applications.

References

[1] M. R. Nanni and J. A. M. Demattê, “Spectral Reflectance Methodology in Comparison to Traditional Soil Analysis,” Soil Sci. Soc. Am. J., vol. 70, no. 2, pp. 393–407, 2006.

[2] A. Allbed and L. Kumar, “Soil Salinity Mapping and Monitoring in Arid and Semi-Arid Regions Using Remote Sensing Technology: A Review,” Adv. Remote Sens., vol. 2, pp. 373–385, 2013.

[3] G. Cruz-Cárdenas, L. López-Mata, C. A. Ortiz-Solorio, J. L. Villaseñor, E. Ortiz, J. T. Silva, and F. Estrada-Godoy, “Interpolation of mexican soil properties at a scale of 1:1,000,000,” Geoderma, vol. 213, pp. 29–35, 2014.

[4] M. Mehrabanian, “Study and comparison of some geostatistical methods for mapping cation exchange capacity (Cec),” Annals of Faculty Engineering HUNEDOARA International
[5] W. Shi, J. Liu, Z. Du, and T. Yue, “Development of a surface modeling method for mapping soil properties,” J. Geogr. Sci., vol. 22, no. 4, pp. 752–760, 2012.

[6] M. S. Simakova, “Small-scale soil mapping,” Eurasian Soil Sci., vol. 44, no. 9, pp. 1036–1038, 2011.

[7] T. P. Robinson and G. Metternicht, “Testing the performance of spatial interpolation techniques for mapping soil properties,” Comput. Electron. Agric., vol. 50, no. 2, pp. 97–108, 2006.

[8] P. Krasilnikov, F. Carre, and L. Montanarella, “Soil geography and geostatistics Concepts and Applications,” European Commission, Joint Research Centre, Institute for Environment and Sustainability, vol. 117, no. 2, 2008.

[9] R. J. Yao, J. S. Yang, and H. B. Shao, “Accuracy and uncertainty assessment on geostatistical simulation of soil salinity in a coastal farmland using auxiliary variable,” Environ. Monit. Assess., vol. 185, no. 6, pp. 5151–5164, 2013.

[10] E. Bijanzadeh, M. Mokarram, and R. Naderi, “Applying spatial geostatistical analysis models for evaluating variability of soil properties in eastern Shiraz, Iran” Iran Agricultural Research, vol. 33, no. 2, pp. 35–46, 2014.

[11] J. Li and A. D. Heap, “Environmental modelling and software spatial interpolation methods applied in the environmental sciences: A review,” Environ. Model. Softw., vol. 53, pp. 173–189, 2014.

[12] W. Shi, J. Liu, Z. Du, A. Stein, and T. Yue, “Surface modelling of soil properties based on land use information,” Geoderma, vol. 162, no. 3–4, pp. 347–357, 2011.

[13] K. Poshtmasari, Z. T. Sarvestani, B. Kamkar, S. Shataei, and S. Sadeghi, “Comparison of interpolation methods for estimating pH and EC in agricultural fields of golestan province,” Int. J. Agric. Crop Sci., vol. 4, no. 4, pp. 157–167, 2012.

[14] S. Maroju, “Evaluation of Five GIS Based Interpolation Techniques for Estimating the Radon Concentration for Unmeasured Zip Codes in the State of Ohio,” A thesis submitted as partial fulfilment of the requirements for the masters of science degree in civil engineering University of Toledo, 2007.

[15] J. Li and A. D. Heap, “A Review of Spatial Interpolation Methods for Environmental Scientists” Geoscience Australia, Record 2008/23, 137 pages, 2008.

[16] B. Attaeian, B. Farokhzadeh, D. Akhzari, and M. M. Artimani, “Comparing interpolation methods for estimating spatial distribution of topsoil pH and EC (Case Study : Karimabad Rangelands , Hamadan Province , Iran ),” ECOPERSIA, vol. 3, no. 4, pp. 1145–1159, 2016.

[17] G. Sankar, P. Kumar, and R. Maiti, “Comparison of GIS-based interpolation methods for spatial distribution of soil organic carbon (SOC),” J. SAUDI Soc. Agric. Sci., 2016, article in press.

[18] M. Zeki and E. Sertel, “Analysis of Different Interpolation Methods for Soil Moisture Mapping Using Field Measurements and Remotely Sensed Data,” International Journal of Environment and Geoinformatics, Vol: 3(3), 11-25, no. 3, 2016.

[19] Y. Xie, T. Chen, M. Lei, J. Yang, Q. Guo, B. Song, and X. Zhou, “Chemosphere Spatial distribution of soil heavy metal pollution estimated by different interpolation methods: Accuracy and uncertainty analysis,” Chemosphere, vol. 82, no. 3, pp. 468–476, 2011.

[20] A. Beucher, R. Siemssen, S. Fröjdö, P. Østerholm, A. Martinkauppi, and P. Edén, “Geoderma Artifi cial neural network for mapping and characterization of acid sulfate soils: Application to Sirppujoki River catchment, Southwestern Finland,” Geoderma, vol. 247–248, pp. 38–50, 2015.

[21] D. Martin and A. Jord, “Spatial models for monitoring the spatio-temporal evolution of ashes after fire – a case study of a burnt grassland in Lithuania,” Solid Earth, vol. 4, pp. 153–165, 2013.

[22] C. G. Karydas, I. Z. Gitas, E. Koutsogiannaki, and N. Lydakis-simantiris, “Evaluation of spatial interpolation techniques for mapping agricultural topsoil properties in Crete,” EARSELeProceedings, vol. 8, pp. 26–39, 2009.

[23] H. N. Ucan and S. Dursun, “Environmental problems of Tuz lake ( Konya-Turkey ) “J. Int. Environmental Application & Science,” vol. 4, no. 2, pp. 231–233, 2009.

[24] O. Mergen and C. Karacaoglu, “Tuz Lake Special Environment Protection Area, Central Anatolia,”
Turkey: The EUNIS Habitat Classification and Habitat Change Detection between 1987 and 2007,” Ekoloji, vol. 9, pp. 1–9, 2015.

[25] T. Gorji, E. Sertel, and A. Tanik, “Monitoring soil salinity via remote sensing technology under data scarce conditions: A case study from Turkey,” Ecol. Indic., vol. 74, pp. 384–391, 2017.

[26] G. N. Tug and F. Duman, “Heavy metal accumulation in soils around a salt lake in Turkey,” Pak. J. Bot. vol. 42, no. 4, pp. 2327–2333, 2010.

[27] Tuz Lake Report, Final Report of the Project on the Determination of Alternative Agricultural Practices and Quality Classification of Soil and Land at Tuz Lake Special Protection Area, TR Ministry of Environment and Forestry- General Directorate of Special Environmental Protection Agency and Ankara Research Institute under the former General Directorate of Village Affairs, Ankara, 391 pages, 2004.

[28] J. Benton and J. R. Jones, “Plant nutrition and soil fertility manual, second edition,” Taylor and Francis Group, LLC, International standard book number-13: 978-1-4398-1610-3, 304 pages, 2012.

[29] K. Johnston, J. M. Ver Hoef, K. Krivoruchko and N. Lucas, “Using ArcGIS geostatistical analyst,” ESRI, 306 pages, 2003.

[30] H. K. Poshtmasari, Z. T. Sarvestani, and B. Kamkar, “Comparison of interpolation methods for estimating pH and EC in agricultural fields of Golestan province (north of Iran),” International Journal of Agriculture and Crop Sciences, vol. 4, no. 4, 157-167, 2012.