2022

BOOK OF PROCEEDINGS

INTERNATIONAL SOIL SCIENCE SYMPOSIUM on

SOIL SCIENCE & PLANT NUTRITION

(7th International Scientific Meeting)

2 – 3 December 2022

Samsun, Türkiye

Editors

Dr.Rıdvan KIZILKAYA
Dr.Coşkun GÜLSER
Dr.Orhan DENGİZ

Organized by

Federation of Eurasian Soil Science Societies
Erasmus Mundus Joint Master Degree in Soil Science (emiSS) Programme

emiSS Master

With the support of the Erasmus+ Programme of the European Union

Cover design by FESSS

Editors:

Dr.Rıdvan Kızılkaya
Ondokuz Mayıs University, Faculty of Agriculture
Department of Soil Science and Plant Nutrition
55139 Samsun, Türkiye

Dr.Coşkun Gülser
Ondokuz Mayıs University, Faculty of Agriculture
Department of Soil Science and Plant Nutrition
55139 Samsun, Türkiye

Dr.Orhan Dengiz
Ondokuz Mayıs University, Faculty of Agriculture
Department of Soil Science and Plant Nutrition
55139 Samsun, Türkiye

ISBN 978-605-63090-8-3

This Book of Proceedings has been prepared from different papers sent to the symposium secretary only by making some changes in the format. Scientific committee regret for any language and/or aim-scope.

Publication date : 10 December 2022

Visit the Symposium web site at
http://www.fesss.org/

E-mail: symposium@fesss.org

International Symposium

EURASIANSOIL
Symposium2022

Soil Science and Plant Nutrition

COMMITTEES

Organizing Committee

CHAIR(S) OF ORGANIZING COMMITTEE


Dr.Rıdvan KIZILKAYA
Türkiye , Chair


Dr.Coskun GÜLSER
Türkiye , Vice-Chair


Dr.Orhan DENGİZ
Türkiye , Vice-Chair

MEMBER(S) OF ORGANIZING COMMITTEE


Dr.Agnieszka JÓZEFOWSKA
Poland


Dr.Ammar ALBALASMEH
Jordan


Dr.Andon ANDONOV
Bulgaria


Dr.Ivan MANOLOV
Bulgaria


Dr.Lesia KARPUK
Ukraine


Dr.Maira KUSSAINOVA,
Kazakhstan


Dr.Maja MANOJLOVİĆ
Serbia


Dr.Markéta MIHALIKOVA
Czech Republic


Dr.Michał GĄSIOREK
Poland


Dr.Svetlana SUSHKOVA
Russia


Dr.Tatiana MINKINA
Russia


Dr.Tomasz ZALESKI
Poland


Dr.Ulviyya MAMMADOVA
Azerbaijan


Dr.Zhanna S. ALMANOVA
Kazakhstan

SECRETARY OF SYMPOSIUM


Res.Ass. Abdurrahman AY
Türkiye


Res.Ass. Salih DEMİRKAYA
Türkiye

Board of FESSS

MANAGEMENT

Dr.Garib MAMMADOV
President, President of Azerbaijan Soil Science Society
Azerbaijan National Academy of Science, Azerbaijan

Dr.Ayten NAMLI
President of Turkish Soil Science Society / Ankara University, Türkiye

Dr.Rıdvan KIZILKAYA
General Secretary
Ondokuz Mayıs University, Türkiye

Dr.Mustafa MUSTAFAYEV
Vice President / Institute of Soil Science and Agrochemistry, Baku, Azerbaijan

Dr.Konul GAFARBAYLI
Representative of Azerbaijan Soil Science Society / Institute of Soil Science and Agrochemistry, Baku, Azerbaijan

Dr.Beibut SULEIMENOV
Representative of Kazakhstan Soil Science Society / Kazakh Research Institute of Soil Science and Agrochemistry, Kazakhstan

Dr.Sergei SHOBA
President of Russian Soil Soil Science Society / Lomonosov Moscow State University, Russia

Dr.Boško GAJİĆ
President of Serbian Soil Soil Science Society / University of Belgrade, Serbia

Dr.Hamid ČUSTOVIĆ
President of Bosnia & Herzegovina Soil Science Society / University of Sarajevo, Bosnia & Herzegovina

Dr.Ermek BAIBAGYSHOV
President of Kyrgyzstan Soil Science Society / Naryn State University, Kyrgyzstan

Scientific Committee

Dr.Alexander MAKEEV, Russia
Dr.Aminat UMAROVA, Russia
Dr.Amrakh I. MAMEDOV, Azerbaijan
Dr.Ayhan HORUZ, Türkiye
Dr.Ayten NAMLI, Türkiye
Dr.Benyamin KHOSHNEVİSAN, China
Dr.Brijesh Kumar YADAV, India
Dr.Carla FERREIRA, Sweden
Dr.David PINSKY, Russia
Dr.Evgeny SHEIN, Russia
Dr.Fariz MIKAILSOY, Türkiye
Dr.Füsun GÜLSER, Türkiye
Dr.Galina STULINA, Uzbekistan
Dr.Guilhem BOURRIE, France
Dr.Guy J. LEVY, Israel
Dr.Gyozo JORDAN, Hungary
Dr.H. Hüsnü KAYIKÇIOĞLU, Türkiye
Dr.Haruyuki FUJIMAKI, Japan
Dr.Hassan EL-RAMADY, Egypt
Dr.Hayriye IBRIKCI, Türkiye
Dr.İbrahim ORTAŞ, Turkey
Dr.İmanverdi EKBERLİ, Turkey
Dr.İzzet AKÇA, Türkiye
Dr.Jae YANG, South Korea
Dr.János KÁTAI, Hungary
Dr.Jun YAO, China
Dr.Kadir SALTALI, Türkiye
Dr.Lia MATCHAVARIANI, Georgia
Dr.Maja MANOJLOVIC, Serbia
Dr.Markéta MIHALIKOVA, Czech Republic
Dr.Metin TURAN, Türkiye
Dr.Mohammad A. HAJABBASI, Iran
Dr.Mustafa BOLCA, Türkiye
Dr.Nicolai S. PANIKOV, USA
Dr.Nikolay KHITROV, Russia
Dr.Niyaz Mohammad MAHMOODI, Iran
Dr.Nutullah ÖZDEMİR, Türkiye
Dr.Pavel KRASILNIKOV, Russia
Dr.Ramazan ÇAKMAKÇI, Türkiye
Dr.Ritu SINGH, India
Dr.Saglara MANDZHIEVA, Russia
Dr.Sait GEZGİN, Türkiye
Dr.Saoussen HAMMAMI, Tunisia
Dr.Sezai DELİBACAK, Türkiye
Dr.Shamshuddin JUSOP, Malaysia
Dr.Sokrat SINAJ, Switzerland
Dr.Srdjan ŠEREMEŠIĆ, Serbia
Dr.Svatopluk MATULA, Czech Republic
Dr.Svetlana SUSHKOVA, Russia
Dr.Taşkın ÖZTAŞ, Türkiye
Dr.Tatiana MINKINA, Russia
Dr.Tayfun AŞKIN, Türkiye
Dr.Velibor SPALEVIC, Montenegro
Dr.Victor B. ASIO, Philippines
Dr.Vishnu D. RAJPUT, Russia
Dr.Vít PENIZEK, Czech Republic
Dr.Yakov PACHEPSKY, USA
Dr.Yury N. VODYANITSKI, Russia

International Symposium
EURASIANSOIL Symposium2022
Soil Science and Plant Nutrition

CONTENTS

Contents

International Symposium on "Soil Science and Plant Nutrition"
Federation of Eurasian Soil Science Societies Cooperation with Erasmus Mundus Joint Mundus Degree in Soil Science (emiSS) Programme
2-3 December 2022 / Samsun, Türkiye
With the support of the Erasmus + Programme of the European Union

State of art approaches, insights, and challenges for digital mapping of electrical conductivity as a dynamic soil property

Fuat KAYA [a], Caner FERHATOĞLU [b], Yavuz Şahin TURGUT [c], Levent BAŞAYİĞİT [a,*]
[a] Faculty of Agriculture, Department of Soil Science and Plant Nutrition, Isparta University of Applied Sciences, 32260 Isparta, Çünür, Türkiye
[b] Department of Agronomy, Iowa State University, Ames, IA 50011, USA
[c] Faculty of Agriculture, Department of Soil Science and Plant Nutrition, Çukurova University, Adana, Türkiye

***Corresponding Author**

Fuat Kaya
fuatkaya@isparta.edu.tr

Abstract
Soil electrical conductivity (EC) as a measure of soil salt content is a good indicator of nutrient and water availability or excessiveness in soils, which in return affect the productivity of soils. Therefore, mapping the spatial distribution of EC under intense agricultural management is important for managing soil fertility (e.g., fertilization and soil salinity remediation). However, mapping soil EC with high accuracy and spatial resolution remains to be challenge among digital soil mappers due to being a highly dynamic soil property. In this study, random forest (RF) was applied to map soil EC in an agricultural plain around the lake Manyas in the northwestern Türkiye. Fifty soil samples and a unique set of environmental predictors (aka covariates) were used to build a predictive soil EC model. The covariates were produced from Sentinel-2 optical satellite images-based vegetation and salinity indices as well as produced from Sentinel-1 with different polarizations (i.e., VV and VH), and terrain attributes representing the topography at varying scales were produced. Twelve environmental variables were selected to be relevant to predicting soil EC after using a correlation-based feature selection procedure. Resulting model performance was evaluated by root-mean-square-error (RMSE) of 10-fold cross-validation (CV). RF predicted soil EC with an RMSE of 0.07 dS m^{-1}. Per each soil prediction in the final soil EC map, an uncertainty map was created using a sensitivity-based approach. The uncertainty map revealed the areas that were more difficult to accurately predict. Present study successfully mapped soil EC with acceptable error and can provide useful insights for managing soil fertility. In addition, an uncertainty map of soil EC can facilitate future soil sampling campaigns. For nearly a quarter of a century, while satellite-based remote sensing data has become the first choice for generating and updating soil survey information, in the near future, artificial intelligence techniques (e.g., ML) will be able to accompany soil surveyors in drawing map boundaries, especially in updating soil salinity phases.

Keywords: Digital soil mapping, random forest, soil electrical conductivity, dynamic soil property, uncertainty.

Introduction
Spatial modeling of soil dynamic properties in arable lands is essential for agricultural management and decision-making (Ning et al., 2022). However, digital maps created for dynamic soil properties with the sufficient accuracy and spatial resolution is particularly rare for the areas where there is intensive agriculture (Baltensweiler et al., 2021). On the other hand, rapid increase in the environmental datasets that could represent soil formation factors (Burke et al., 2021) has made it easier to map soil dynamic properties using digital soil mapping (DSM) framework (Flynn et al., 2022). DSM refers to the creation of soil maps based on the relationships between environmental datasets (aka covariates) and mesaured soil data using statistical

learning algorithms (e.g., machine learning (ML)) (McBratney et al., 2003). In recent years, machine learning (ML) approach has been rapidly adopted in the prediction of soil properties (Hengl and MacMillan, 2019). Despite the succesful use examples of ML algorithms in mapping soil dynamic properties, large variations of soil EC and its highly dynamic nature at the field scale makes it difficult to predict soil EC accurately. This is typically due to its high dependence on agricultural activities as well as soil formation factors (Jenny, 1941). Current approaches to capture this variation have witnessed field-based studies specific to many different ML algorithms (Tomaz et al., 2020; Hateffard et al., 2022). Since EC is seen as a surrogate of soil salinity in the literature, studies are focused on predicting areas where salinity threats may develop. (Hopmans et al., 2021). This study aimed to digitally map the spatial distribution of soil EC using RF ML algorithm, using the environmental covariates satellite imagery products and digital terrain attributes derived from a digital elevation model (DEM) with varying analyis scales. An associated uncertainty map was also created to improve credibility of resultant soil EC map.

Material and Methods

Study area, sampling, and analyses

The study field was located around the lake Manyas and covered an undulating area of 59 928 ha (N35 Zone UTM, 570000-595000 East, 4440000-4460000 North). The climatic conditions are characterized by an average annual temperature of 15°C and annual precipitation of about 700 mm (TSMS, 2022). The current area is rainfed marginal lands in the north of the study area in Vertisols, and essential and marginal irrigated complex agricultural areas in the south and west, according to field surveys. Fifty soil samples according to the stratified random sampling method at a depth of 30 cm were taken from the research area between June and August of 2019. The soil samples were air-dried at a room temperature of 24°C without a direct exposure to sunlight, ground, and then sieved with a 2 mm sieve. The processed samples were mixed with water to make a soil solution (the ratio of soil to water is 1:5) according to FAO (2021). After the solution was shaken for 1 hour (180 osc./min), EC (1:5 w/v, dS m^{-1}) of soil samples was measured by a conductivity meter (Orion Star A112; Thermo Fisher Scientific). Duplicate analysis was performed on randomly selected 20 % of all samples in a test group. Relative Percent Difference (RPD) was calculated to determine whether the precision of duplicate analyzes was within specification. In many cases, RPDs of replicate pairs were less than 5%. Average RPD for the replicates was 5.66%, which was below the standard rule of 20% determined by FAO (2021).

Environmental covariates

In this study, nineteen environmental variables was used to model soil EC. The variables were from the European Space Agency's (ESA) Sentinel-2A satellites (ESA, 2015) (and corresponding spectral indices), ESA's Sentinel-1 Synthetic Aperture Radar (SAR), and digital terrain attributes (DTAs) created by using the digital elevation model (DEM) from Shuttle Radar Topography Mission (SRTM). DEM and satellite imagery products were downloaded using google earth engine (GEE). These imagery products were useful to represent soil formation factors that could be influential in the spatial distribution of soil EC in our study area (Jenny, 1941). Sentinel-2A imagery represented organisms through providing information about the conditions of vegetation. Sentinel-1 SAR imagery in both VV and VH polarizations was obtained as the average of the relevant month of the year of the sampling date within the boundaries of the study area to indirectly represent climate through providing information about soil moisture (ESA, 2012). Soil EC is especially known to be affected by soil moisture (Taghadosi et al., 2019).

Varying analysis scales (i.e., 130 m to 1010 m) were used to calculate the DTAs based on the pixel values of DEMs using the r.param.scale function in GRASS GIS 7.6.1 (Geographic Resources Analysis Support System, available online: grass.osgeo.org, accessed on 3 July 2022). As land-surface derivatives are dependent on the scale for calculation (Roecker and Thompson, 2010), different analysis scales may result in different outcomes. The use of DTAs with varying analysis scales as potential environmental predictors is useful because different analysis scales may be more appropriate for representing various phenomena (Miller et al., 2015) (Table 1). Since all covariates were obtained from different sources and have the different spatial resolutions, all covariates were aligned to the same grid cell resolution (10 m) and extent before constructing the data matrix. Complete list of environmental covaraites used in this study can be found in Table 1.

Table 1. The specifications of used covariates derived by DEM and remote sensing imageries in this study.

Environmental covariates			
Digital Terrain Attributes		**Produced via program**	
Elevation (m) Slope (%) Aspect (°) Topographic wetness index		SAGA 8.4.0 (Conrad et al., 2015)	
Longitudinal Curvature Cross-sectional curvature		GRASS GIS 7.8.7 (GRASS Development Team, 2022)	
Remote Sensing (RS) (Sentinel-2A) Optical Based (Accessed to three satellite image close to the sampling date in 2019)			
Vegetation-soil based indices	Equations (Brown et al., 2017; Mponela et al., 2020)	Salinity indices	Equations (Avdan et al., 2022)
GRVI	$\frac{(Green-Red)}{(Green+Red)}$ [1]	SI 1	$\sqrt{Blue \times Red}$ [6]
SatInd	$\frac{(Red-Blue)}{(Red+Blue)}$ [2]	SI 2	$\sqrt{Green \times Red}$ [7]
NDVI	$\frac{(Near\ Infrared-Red)}{(Near\ Infrared+Red)}$ [3]	SI 3	$\frac{(Blue-Red)}{(Blue+Red)}$ [8]
CI	$\frac{(Red-Green)}{(Red+Green)}$ [4]	SI 4	$\frac{Green \times Red}{Blue}$ [9]
GNDVI	$\frac{(Near\ Infrared-Green)}{(Near\ Infrared+Green)}$ [5]	SI 5	$\frac{Blue \times Red}{Green}$ [10]
		SI 6	$\frac{Near\ Infrared \times Red}{Green}$ [11]
Remote Sensing (RS) (Sentinel-1 SAR) synthetic aperture RADAR Based			
VV-Vertical transmit, Vertical receive polarisation VH- Vertical transmit, Horizontal receive polarisation			

Abbreviations: GRVI: Green-Red vegetation index, SatInd: Saturation index, NDVI: Normalized difference vegetation index, CI: Coloration Index, GDVI: Green Normalized Difference Vegetation Index, SI: Salinity Index. With GRASS GIS, magnitude of maximum gradient was taken as the calculation basis for slope, aspect, cross-sectional curvature.

A trial-error based feature selection (FS) process was carried out to overcome the multi-collinearity and curse of dimensionality issues (Ferhatoglu and Miller, 2022). Correlated covariates were removed by using Pearson's r of 0.8 while keeping only one of the correlated covariates. The final selection of environmental covariates determined was 12 variables.

Modelling and creation of digital maps

Overall workflow of this study is shown in Figure 1. RF-based regression analysis was used to model and map the spatial distribution of soil EC. The RF algorithm is known to be advantegous because input data to be used in RF algorithm does not make assumption about the normality of the input data (Velázquez et al., 2022). Thus, the original data was directly used in the modeling. In addition, RF algorihtm has been succesfully applied in the prediction of dynamic soil properties (Kaya and Basayigit, 2022).

Using the *randomForest* (Liaw and Wiener, 2002) function in the R Core Environment (R version 3.6.1) (R Core Team 2022) and RStudio IDE (RStudio 2022), the EC of the surface soil in the study area was estimated using a laboratory soil analysis set and environmental covariates. Multiple models were created by the process of 10-fold CV. The average outcomes of these models were used to create the final soil EC map, using the "mean" base function in randomForest function. As error metrics in creation of decision trees by RF algorithm, %IncMSE and IncNodePurity metrics were used. %IncMSE was calculated for each tree with and without the relevant predictors, the mean value of the differences being normalized to the standard deviation of the differences. IncNodePurity represented the average overall trees of the total reduction in node impurity from splitting among a predictor in the tree-building process.

Assessment of model performance and uncertainty measurement

RF algorithm with 10-fold CV was used to create uncertainty map for soil EC, splitting all samples into calibration (75% of all samples) and validation (25% of all samples) sets during each of ten iterations. In each iteration, a model-building and prediction process is carried out in such a way that the distribution of the predicted values at the pixel level represents the uncertainty and the sensitivity of the model to changes in the current dataset (Yigini et al., 2018). Coefficient of determination (R^2), Root mean square error (RMSE) is obtained for each iteration. The standard deviation (sd) of all ten predictions allowed the model sensitivity to be mapped, using the limited available sample set used this study.

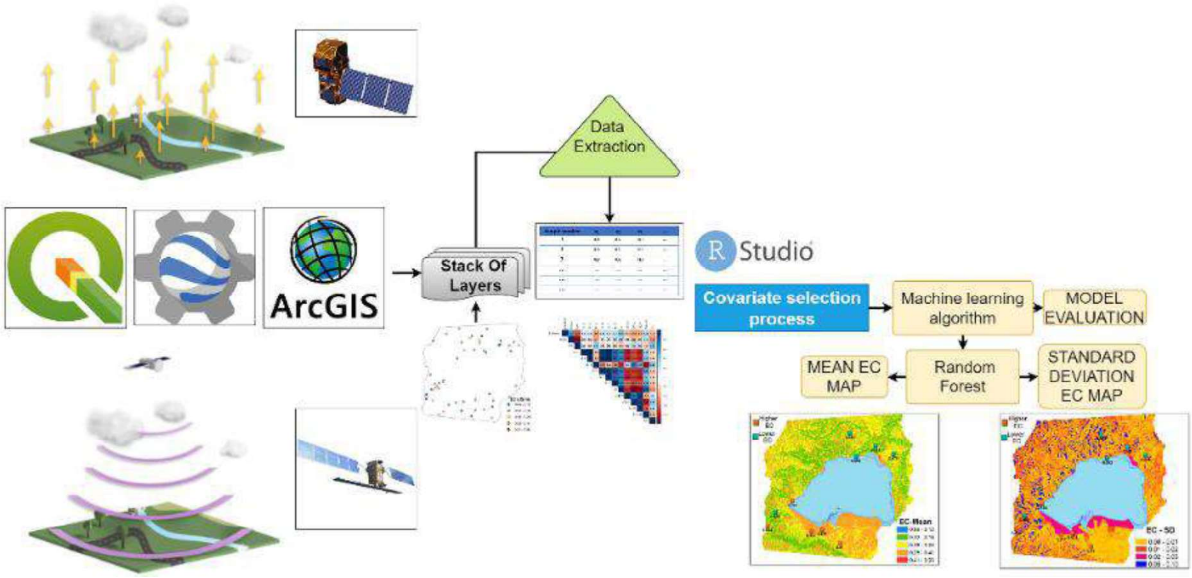

Figure 1. Overall workflow in this study to map soil EC.

Results and Discussion

Descriptive statistics of soil data

Soils of the study area were slightly or non-saline with a mean of 0.2 dS m^{-1} (Table 2) according to the criterion determined in Omuto et al. (2020). Soil EC values of the study area indicate that long-term land use could affect soil EC (Figure 2-c). Exceptionally, high EC values in the study area (Figure 2-b) were found in the soils that in the marginal irrigated lands. These areas were also used for intensive agriculture. Therefore, the surface EC, which is a dynamic soil property, can show high variability over short distances with intensive organic or chemical fertilization in marginal irrigated lands. To quantify the correlations between soil EC and environmental covariates, Spearman's correlation values were calculated (Figure 2-a). While there was a negative correlation between EC and Elevation in our study area (r = -0.32, p<0.05), EC showed a positive correlation with TWI (r = 0.43, p<0.05). There was a positive correlation between vegetation-based indices and EC (GNDVI r=0.20, GRVI r=0.39, p<0.05). Negative correlations were detected between salinity indices and EC values, ranging from r=-0.21 to r=-0.25 (p<0.05). Positive (r=0.27, p<0.05) relationships were determined between S1VV and EC in SAR data and these findings are compatible with literature (Triphati and Tiwari 2021) (Figure 2).

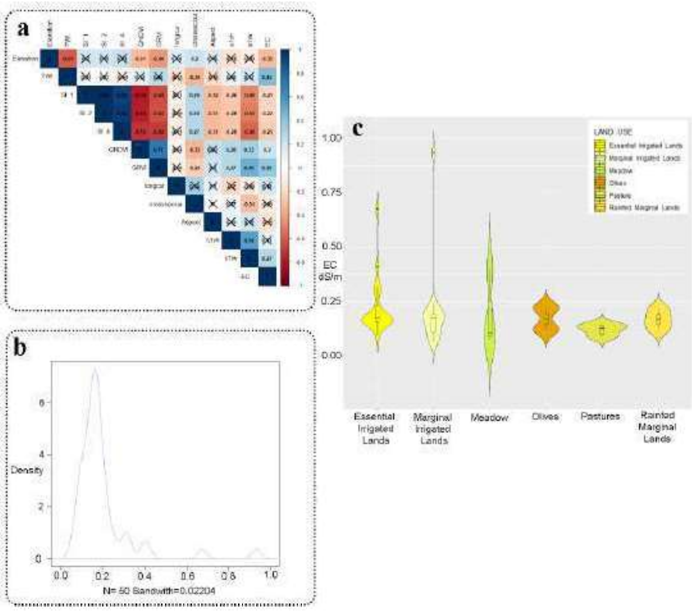

Figure 2. The statistical descriptive statistics of used field observations across the study area. a) correlation graph-Spearman correlation coefficient values of the dependent variable (EC) with predictive environmental variables (p < 0.05), b) Density plot of the dependent variable (EC), c) Violin graph- Comparison of EC values of soil samples according to land uses.

Table 2. Descriptive statistics of soil EC based on all samples (50).

	Mean	SD	CV	Minimum	Median	Maximum	Skewness	Kurtosis
Soil EC (dS m^{-1})	0.20	0.15	73.85	0.06	0.17	0.93	3.40	13.94

Abbreviations: SD: Standard deviation, CV: Coefficient of Variation (%).

Performance of spatial predictions and quantified uncertainties

RF algorithm allowed us to identify the relationships between soil EC and selected environmental covariates and leverage these relationships to create a soil EC map. Modeling and mapping were executed using R-studio (version: 2022.07.2). The model performance criteria in the data set used at the end of the modelling process carried out in 10 iterations for this study are presented in Table 3. As a result of the modeling, prediction accuracy of soil EC was determined to be acceptable with an average RMSE of 0.07-0.08 dS m^{-1} CV performance.

Table 3. The performance of the RF model for estimating soil EC across the study area based on R^2 and RMSE of a 10-fold CV. Variation among the performance based on the created models from different folds were presented by minumum, median, mean, and maximum values.

			10-fold Cross-validation results			
			Used random samples of 75%		Used random samples of 25%	
Soil property		Model	R^2	RMSE dS m^{-1}	R^2	RMSE dS m^{-1}
EC	RF	Minimum	0.50	0.03	0.79	0.06
		Median	0.85	0.05	0.88	0.08
		Mean	0.81	0.07	0.88	0.08
		Maximum	0.94	0.11	0.91	0.09

Evaluating with soil surveyor's insight how to evaluate maps beyond point estimation is an important contribution to the advancement of soil mapping as a science.In this regard, some of the important observations in our data were as follows: 1) Across the study area, areas with high soil EC values were very limited (Figure 3-B). To allow the qualitative evaluation of the soil surveyor, spatial maps were presented by zooming in on the points with higher and lower soil EC values using a geographical information system (GIS) (Figure 3-A, C). Land use images at the time of soil samples were also referenced for qualitative assessment (Figure 3-D-E). As a result of zooming in on the point with the highest EC value among all samples, it was observed that the high soil EC values in the surrounding pixels were detected by the RF algorithm (Figure 3-A). Considering the land use image of this area supported the judgement of the areas around this soil sample (with high soil EC) as the areas with intensive agriculture. In the areas with intensive agriculture, to use detailed land use data as input to the models for the prediction of a dynamic soil property is recommended.

An approach specific to the current study is demonstrated to estimate the sensitivity of the model to available data (spatial pattern of environmental variables) and the uncertainty of the ML models (Figure 5-B). Lands with complex soil formation, such as our study area, which was characterized by large plains, are often characterized by strong multifactorial interactions, non-linearity, and non-stationarity in data relationships. This makes it challenging to predict soil dynamic properties easily due to highly dynamic nature of soils in such lands. Despite that, the RF algorithm produced reasonable estimates for the mean soil EC maps (Figure 3-B) within the areas that had relatively low and high soil EC values. However, the uncertainty map (Figure 5-B) usually showed large standard deviation values for such areas. This indicated that current selection of environmental covariates or the quantity of soil samples were insufficient to reliably map the spatial variation of soil EC in those portions of the study area.

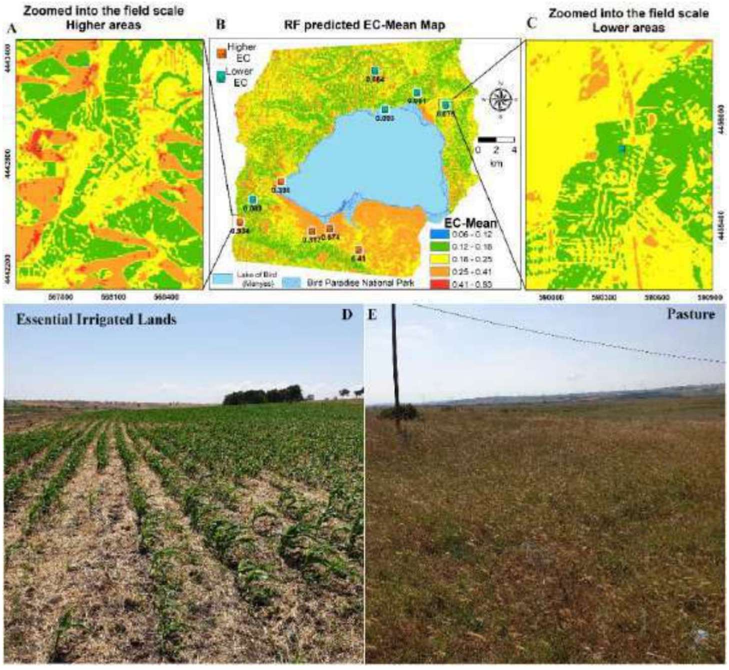

Figure 3. Mean maps of the predicted soil EC (dS m^{-1}) derived from ten times random forest (RF) models (B). (A) Zoomed in on higher areas and (C) zoomed in on lower areas. Fotographs were taken from different areas of the study area in July 2019 (D-E). Photo credit: Fuat KAYA, 2019-July, Manyas, Balıkesir, Türkiye.

To provide information about the reliability of soil EC predictions, it is suggested that the areas with high standard deviation values need to be emphasized. Many other scientists also pointed out the importance of uncertainity maps when mapping soil dynamic properties for local areas with high soil heterogeneity or small sample sizes (Liu et al., 2022). As decision-makers often prefer to define the areas with sharp boundaries (such as the topsoil salinity phase in soil survey), the presentation and use of uncertainty maps are highly needed for improving the decision-making process (Arrouays et al., 2020).

Relative importance of environmental variables

Relative importance of the covariates in modeling was assessed according to RF's %IncMSE and IncNodePurity metrics (Figure 4). Topographic covariates such as elevation and TWI were identified as the most important variables in the estimation of soil EC. The covariate Aspect had the highest level of IncNodePurity value, which meant that Aspect was the least useful predictor in mapping soil EC in our study. Interestingly, the areas with extreme Aspect values in the study area matched the areas with the highest standard deviation or uncertainty (Figure 5-B).

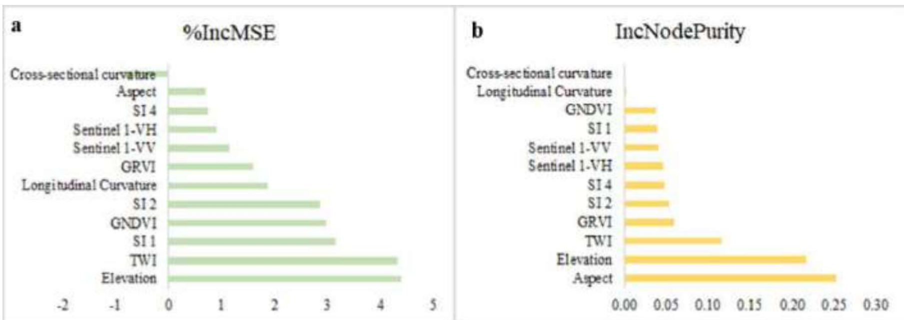

Figure 4. Relative importance by RF algorithm for the covariates to predict soil EC: a) %IncMSE, b) IncNodePurity.

Lower light intensity, evaporation, air and soil temperatures were usually observed on shaded hillsides. The change between soil freezing and thawing was also less frequent on shady hillsides relative to the sunny sides. As a result, soils on shaded hillsides exhibited stronger and deeper water penetration than those on generally more sunny hillsides. However, the dissociation intensity was lower on colder shaded hillsides. Similar results were also found in other studies (Blume et al. 2016). The current study area exhibited an undulating formation. The difference in the numerical values of the "aspect" variable in the" undulating" physiographic structure in our study area may be effective in the natural change of the EC value. However, covariates related to farming history (e.g., tillage, fertilization, cropping system) can be useful to be included in modeling that were not present in our study.

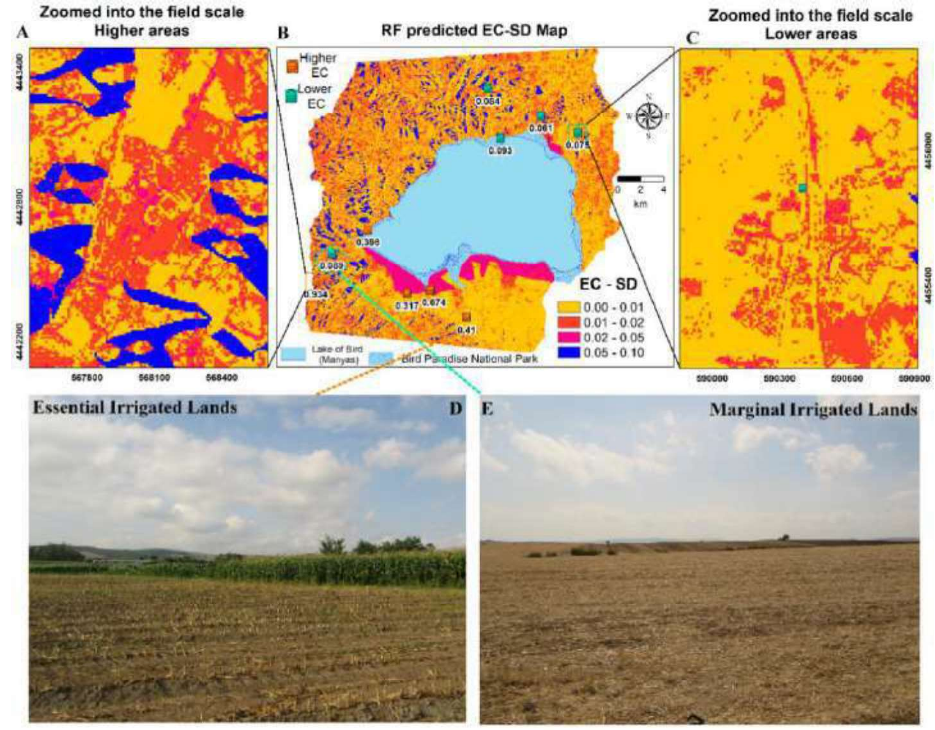

Figure 5. (B) Uncertainty maps by standard deviation of the predicted soil EC (dS m-1) derived from running RF algorithm ten times with CV. (A) Zoomed in on higher areas and (C) zoomed in on lower areas. (D&E) The fotographs were taken from different locations within the study area in July 2019 using a digital camera. Photo credit: Fuat KAYA, 2019-July, Manyas, Balıkesir, Türkiye.

Conclusion

Soil EC is one of the dynamic soil properties. It should always be determined in the most up-to-date form. EC data can be obtained from soil maps that are not up-to-date and be produced with coarse-resolution conventional approaches.In this study, there is the production of a digital soil EC map based on soil analysis with 50 samples.The process was performed by integrating the RF algorithm and a detailed digital surrogate of soil formation factor in a high-performance computational environment with adaptive quantification of the predictive soil mapping paradigm over a large area with complex soil dynamics.In the study, the associated uncertainty map for soil EC predictions was successfully generated.Spatial information about soil EC created in this study can provide remarkable insights into decision-making processes aligning with the increasing need for soil information for sustainable development goals in the future.The approach proposed in the study may be an opportunity for the production of the salinity phase in detailed soil maps. In addition, associated uncertainty fields can show priority points in the selection of soil samples for salinity.

References

Arrouays, D., McBratney, A., Bouma, J., Libohova, Z., Richer-de-Forges, A. C., Morgan, C. L. S., Roudier, P., Poggio, L. Mulder, V. L., 2020. Impressions of digital soil maps: The good, the not so good, and making them ever better. Geoderma Reg. 20, e00255. doi:10.1016/j.geodrs.2020.e00255

Avdan, U., Kaplan, G., Küçük Matcı, D., Yiğit Avdan, Z., Erdem, F., Tuğba Mızık, E., Demirtaş, İ., 2022. Soil salinity prediction models constructed by different remote sensors. Phys Chem Earth Parts A/B/C, 128, 103230. doi:10.1016/j.pce.2022.103230

Baltensweiler, A., Walthert, L., Hanewinkel, M., Zimmermann, S., Nussbaum, M., 2021. Machine learning based soil maps for a wide range of soil properties for the forested area of Switzerland. Geoderma Reg. 27, e00437. doi:10.1016/j.geodrs.2021.e00437

Blume, H.P., Brümmer, G.W., Fleige, H., Horn, R., Kandeler, E., Kögel-Knabner, I., Kretzschmar, R., Stahr, K., Wilke, B.M. 2016. Soil Development and Soil Classification. In Blume, H.P., Brümmer, G.W., Fleige, H., Horn, R., Kandeler, E., Kögel-Knabner, I., Kretzschmar, R., Stahr, K., Wilke, B.M. (Eds.), Scheffer/SchachtschabelSoil Science. Springer, Berlin, Heidelberg. pp. 285-389. doi:10.1007/978-3-642-30942-7_7

Brown, K.S., Libohova, Z., Boettinger, J., 2017. Digital Soil Mapping. In: Ditzler, C., Scheffe, K., Monger, H.C. (Eds.), Soil Survey Manual, USDA Handbook 18. Government Printing Office, Washington, D.C, pp. 295–354.

Burke, M., Driscoll, A., Lobell, D. B., Ermon, S., 2021. Using satellite imagery to understand and promote sustainable development. Science 371(6535), eabe8628. doi:10.1126/science.abe8628

Conrad, O., Bechtel, B., Bock, M., Dietrich, H., Fischer, E., Gerlitz, L., Wehberg, J., Wichmann, V., and Böhner, J., 2015. System for Automated Geoscientific Analyses (SAGA) v. 2.1.4, Geosci. Model Dev. 8, doi:10.5194/gmd-8-1991-2015

ESA, 2012. Sentinel-1: ESA's Radar Observatory Mission for GMES Operational Services (ESA SP-1322/1, March 2012). Accessed link: https://sentinel.esa.int/documents/247904/349449/s1_sp-1322_1.pdf

ESA, 2015. Sentinel-2 User Handbook. Accessed link: https://sentinel.esa.int/documents/247904/685211/sentinel-2_user_handbook

FAO. 2021. Standard operating procedure for soil electrical conductivity, soil/water, 1:5. Rome.

Ferhatoglu, C., Miller, B. A., 2022. Choosing Feature Selection Methods for Spatial Modeling of Soil Fertility Properties at the Field Scale. Agronomy 12(8). doi:10.3390/agronomy12081786

Flynn, T., Rozanov, A., Ellis, F., de Clercq, W., Clarke, C., 2022. Farm-scale digital soil mapping of soil classes in South Africa. S. Afr. J. Plant Soil 39(3), 175–186. doi:10.1080/02571862.2022.2059115

GRASS Development Team, 2017. Geographic Resources Analysis Support System (GRASS) Software, Version 7.2. Open Source Geospatial Foundation. Electronic document:. http://grass.osgeo.org

Hateffard, F., Balog, K., Tóth, T., Mészáros, J., Árvai, M., Kovács, Z.A., Szűcs-Vásárhelyi, N., Koós, S., László, P., Novák, T.J., Pásztor, L., Szatmári, G., 2022. High-Resolution Mapping and Assessment of Salt-Affectedness on Arable Lands by the Combination of Ensemble Learning and Multivariate Geostatistics. Agronomy 12(8). doi:10.3390/agronomy12081858

Hengl, T., & MacMillan, R. A., 2019. Predictive soil mapping with R (370 pp.). OpenGeoHub Foundation. www.soilmapper.org

Hopmans, J. W., Qureshi, A. S., Kisekka, I., Munns, R., Grattan, S. R., Rengasamy, P., Taleisnik, E., 2021. Chapter One - Critical knowledge gaps and research priorities in global soil salinity. Adv. Agron. 169, 1–191. doi:10.1016/bs.agron.2021.03.001

Jenny, H., 1994. *Factors of soil formation: a system of quantitative pedology*. Courier Corporation.

Kaya, F., Başayiğit, L., 2022. Using Machine Learning Algorithms to Mapping of the Soil Macronutrient Elements Variability with Digital Environmental Data in an Alluvial Plain. In Artificial Intelligence and Smart Agriculture Applications (pp. 107-136). Auerbach Publications. doi:10.1201/9781003311782-6.

Liu, F., Wu, H., Zhao, Y., Li, D., Yang, J.-L., Song, X., Shi, Z., Zhu, A., Zhang, G.-L., 2022. Mapping high resolution National Soil Information Grids of China. Sci Bull. 67(3), 328–340. doi:10.1016/j.scib.2021.10.013

Miller, B. A., Koszinski, S., Wehrhan, M., & Sommer, M., 2015. Impact of multi-scale predictor selection for modeling soil properties. Geoderma 239–240, 97–106. doi:10.1016/j.geoderma.2014.09.018

Mponela, P., Snapp, S., Villamor, G. B., Tamene, L., Le, Q. B., Borgemeister, C., 2020. Digital soil mapping of nitrogen, phosphorus, potassium, organic carbon and their crop response thresholds in smallholder managed escarpments of Malawi. Appl Geogr. 124, 102299. doi: 10.1016/j.apgeog.2020.102299

Ning, L., Cheng, C., Lu, X., Shen, S., Zhang, L., Mu, S., Song, Y., 2022. Improving the Prediction of Soil Organic Matter in Arable Land Using Human Activity Factors. Water 14(10). doi:10.3390/w14101668

Omuto, C.T., Vargas, R.R., el Mobarak, A.M., Mohamed, N. Viatkin, K., Yigini, Y., 2020. Mapping of Salt-Affected Soils: Technical Manual. 1st ed. FAO, Rome. Available from: http://www.fao.org/3/ca9215en/ca9215en.pdf

R Core Team. 2022. R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. URL https://www.R-project.org/.

Roecker, S., Thompson, J., 2010. Scale Effects on Terrain Attribute Calculation and Their Use as Environmental Covariates for Digital Soil Mapping. In: Boettinger, J.L., Howell, D.W., Moore, A.C., Hartemink, A.E., Kienast-Brown, S. (eds) Digital Soil Mapping. Progress in Soil Science, vol 2. Springer, Dordrecht. doi:10.1007/978-90-481-8863-5_5

RStudio Team. 2022. RStudio: Integrated Development Environment for R. RStudio, PBC, Boston, MA URL http://www.rstudio.com/.

Taghadosi, M. M., Hasanlou, M., Eftekhari, K., 2019. Soil salinity mapping using dual-polarized SAR Sentinel-1 imagery. International Journal of Remote Sens. 40(1), 237–252. doi:10.1080/01431161.2018.1512767

Tomaz, A., Palma, P., Fialho, S., Lima, A., Alvarenga, P., Potes, M., Costa, M.J., Salgado, R., 2020. Risk Assessment of Irrigation-Related Soil Salinization and Sodification in Mediterranean Areas. Water 12(12). doi:10.3390/w12123569

Tripathi, A., Tiwari, R. K., 2021. A simplified subsurface soil salinity estimation using synergy of SENTINEL-1 SAR and SENTINEL-2 multispectral satellite data, for early stages of wheat crop growth in Rupnagar, Punjab, India. Land Degrad Dev. 32(14), 3905–3919. doi:10.1002/ldr.4009

TSMS. 2022. Turkish State Meteorological Service.

Velázquez, F. J. B., Shahabi, M., Rezaei, H., González-Peñaloza, F., Shahbazi, F., Anaya-Romero, M., 2022. The possibility of spatial mapping of soil organic carbon content at three depths using easy-to-obtain ancillary data in a Mediterranean area. Open Res. Eur 2(110). doi:10.12688/openreseurope.14716.1

Yigini, Y., Olmedo, G.F., Reiter, S., Baritz, R., Viatkin, K., Vargas, R., 2018. Soil Organic Carbon Mapping Cookbook 2nd edition. Rome, FAO, p. 220. Available from: https://www.fao.org/3/I8895EN/i8895en.pdf.

International Soil Science Symposium on
"SOIL SCIENCE & PLANT NUTRITION"
(7th International Scientific Meeting)
2-3 December 2022 / Samsun, Türkiye