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Ground Observations and Environmental Covariates Integration for Mapping of Soil Salinity: A Machine Learning-Based Approach

Salman Naimi ¹ , Shamsollah Ayoubi ¹ , Mojtaba Zeraatpisheh ^{2,3,*} and Jose Alexandre Melo Dematte ⁴

¹ Department of Soil Science, College of Agriculture, Isfahan University of Technology, Isfahan 841156-83111, Iran; s.naimi@ag.iut.ac.ir (S.N.); ayoubi@cc.iut.ac.ir (S.A.)

² Henan Key Laboratory of Earth System Observation and Modeling, Henan University, Kaifeng 475004, China

³ College of Geography and Environmental Science, Henan University, Kaifeng 475004, China

⁴ Department of Soil Science, Luiz de Queiroz College of Agriculture, Av. Pádua Dias, 11, Piracicaba 13418-900, SP, Brazil; jamdemat@usp.br

* Correspondence: mojtaba.zeraatpisheh@henu.edu.cn or zeraatpishem@yahoo.com; Tel.: +86-185-6704-1719

Abstract: Soil salinization is a severe danger to agricultural activity in arid and semi-arid areas, reducing crop production and contributing to land destruction. This investigation aimed to utilize machine learning algorithms to predict spatial soil salinity (dS m^{-1}) by combining environmental covariates derived from remotely sensed (RS) data, a digital elevation model (DEM), and proximal sensing (PS). The study is located in an arid region, southern Iran ($52^{\circ}51' - 53^{\circ}02'E$; $28^{\circ}16' - 28^{\circ}29'N$), in which we collected 300 surface soil samples and acquired the spectral data with RS (Sentinel-2) and PS (electromagnetic induction instrument (EMI) and portable X-ray fluorescence (pXRF)). Afterward, we analyzed the data using five machine learning methods as follows: random forest—RF, k-nearest neighbors—kNN, support vector machines—SVM, partial least squares regression—PLSR, artificial neural networks—ANN, and the ensemble of individual models. To estimate the electrical conductivity of the saturated paste extract (ECe), we built three scenarios, including Scenario (1): Synthetic Soil Image (SySI) bands and salinity indices derived from it; Scenario (2): RS data, PS data, topographic attributes, and geology and geomorphology maps; and Scenario (3): the combination of Scenarios (1) and (2). The best prediction accuracy was obtained for the RF model in Scenario (3) ($R^2 = 0.48$ and $RMSE = 2.49$), followed by Scenario (2) (RF model, $R^2 = 0.47$ and $RMSE = 2.50$) and Scenario (1) for the SVM model ($R^2 = 0.26$ and $RMSE = 2.97$). According to ensemble modeling, a combined strategy with the five models exceeded the performance of all the single ones and predicted soil salinity in all scenarios. The results revealed that the ensemble modeling method had higher reliability and more accurate predictive soil salinity than the individual approach. Relative improvement (RI%) showed that the R^2 index in the ensemble model improved compared to the most precise prediction for the Scenarios (1), (2), and (3) with 120.95%, 56.82%, and 66.71%, respectively. We applied the best model in each scenario for mapping the soil salinity in the selected area, which indicated that ECe tended to increase from the northwestern to south and southeastern regions. The area with high ECe was located in the regions that mainly had low elevations and playa. The areas with low ECe were located in the higher elevations with steeper slopes and alluvial fans, and thus, relief had great importance. This study provides a precise, cost-effective, and scientific base prediction for decision-making purposes to map soil salinity in arid regions.

Keywords: soil salinization; machine learning; remote and proximal sensing; Sentinel-2 MSI; SySI; soil health

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1. Introduction

As one of the most common environmental concerns, soil salinization is a severe threat to agricultural activity in arid and semi-arid districts, reducing crop production and

contributing to land destruction [1]. In these areas, lands that are widely irrigated, mainly to improve water use efficiency, the irrigation system has been changed from flood to drip irrigation, which has caused the accumulation of salts in the root zone and surface soil salinization [2]. In the last decades, Iran has faced increasing soil salinization problems due to increasing drought because of climate change consequences and human pressures on land and water resources in this region [3]. Therefore, accurate and reliable salinity mapping is needed to monitor and assess saline soil and manage the issue [4]. However, due to the high spatio-temporal variability in soil salinity, a timely and accurate approach is essential for soil salinity prediction to prevent and control soil degradation and ecological restoration in arid and semi-arid districts [5].

Traditional soil mapping is laborious, expensive, and not suitable to cover extended areas [6]. Using the digital soil mapping (DSM) technique can solve the problems of traditional methods and is a practical alternative [7–10]. Currently, several environmental covariates, including topographic ones, legacy soil maps, and remote sensing (RS) and proximal sensing (PS) data, were applied as auxiliary covariates for predicting soil properties, including soil salinity [4,5], soil organic carbon [11], and soil classes [12] for DSM technique.

McBratney et al. [7] explicated several modeling methods used in DSM investigations. Machine learning algorithms have been extensively applied in DSM to achieve the relationships between the spatial variation of soil characteristics and environmental covariates and then derive the spatial variability of soil attributes. This method is more successful at evaluating non-linear interactions between soil and environmental covariates [13]. Many machine learning algorithms have been assessed for soil properties prediction, including Cubist [14,15], artificial neural networks [16,17], partial least squares regression [18,19], k-nearest neighbors [19], regression kriging [20,21], multinomial logistic regression [12], multiple linear regression [22], random forests [23,24], random forest regression [25], support vector machines [17,26], and genetic algorithms [16].

RS data from satellite images, i.e., the Sentinel-2 Multi-Spectral Instrument (S2-MSI), are commonly used to investigate the spatial variation of soil salinity in agricultural regions and other land resources [27–31]. Meanwhile, PS data are increasingly being utilized to map soils with high spatial resolution in order to support precision agriculture and land management [32,33]. This data comprises measuring soil properties with geophysical field and laboratory sensors in order to directly or indirectly forecast and map soil properties of interest.

Electromagnetic induction instrument (EMI) sensors and portable X-ray fluorescence spectrometry (pXRF) are used to quantify soil properties in situ or in the laboratory. Several researchers have considered apparent electrical conductivity (ECa) as a convenient source of ancillary information for mapping soil salinity [4,34–37]. Additionally, other scholars have used data obtained from pXRF for predicting and mapping soil properties [38–41]. It seems that among the available environmental covariates for mapping soil salinity, the RS and PS techniques using the EMI and pXRF spectrometry have been of significant importance because they are good instruments for prediction, temporal monitoring, and mapping of soil salinity in conjunction with field measurements. However, there is little attempt to combine these two datasets for predicting soil properties, especially soil salinity in arid lands.

In recent years, in most arid and semi-arid regions in Iran, soluble salts have accumulated in the soil surface. The main reasons for this phenomenon are low precipitation and human activities, such as irrigation with saline water (low-quality water), improper water and soil management, overexploitation of groundwater, and insufficient drainage. Moreover, due to a lack of information about the spatial variability of soil salinity, land use planning was conducted inappropriately by decision-makers. As a result, the production of agricultural products has been gradually decreased. Therefore, to manage this problem, regular monitoring of soil salinity and detailed knowledge regarding its spatial distribution is essential [42].

As mentioned, there is little attempt to combine RS data and auxiliary environmental data with PS data to predict soil salinity. Since soil sensing is range-specific with attributes, soil attributes could thus be defined in different spectral ranges. This study expects that PS detects the salinity elements and remotely assists in specialization using the machine learning system. As a result, the main goals of this study were (i) to predict soil salinity spatially by combining RS data and environmental covariates with PS such as EMI and pXRF, (ii) evaluate the capability of different machine learning methods including PLSR, SVM, RF, ANN, kNN, and the ensemble of individual models for predicting soil salinity, and (iii) to determine the most important covariates for predicting soil salinity by sensitivity analysis in an arid region, southern Iran.

2. Materials and Methods

2.1. Description of the Study Area

The study site is located at the Afzar region in Fars province (part of the folded Zagros) south of Iran ($52^{\circ}51'–53^{\circ}02'E$; $28^{\circ}16'–28^{\circ}29'N$) and covers 242 km². Most of the study area is almost flat with a slope of 1–4%, and the elevation varies from 597 to 723 m above sea level (Figure 1). The predominant crops cultivated in the plain included citrus and dates, followed by wheat, barley, maize, and cucurbits. In the study area, the climate is the hot desert climate (BWh in the Köppen–Geiger classification) with a mean annual temperature and precipitation of 22.8 °C and 240 mm, respectively [43]. The precipitation mainly occurs during the cold months (November to March), and the local temperature ranges from −3 °C in January to 43.4 °C in July. The average annual evaporation is 2900 to 3400 mm [44]. The study area comprises various geological units, including deposits consisting of alluvial deposits, limestone, shale, and marl [45] (Figure 1a). The soils of the northern parts of the region are mainly from silty, sand, and clay flats (Q_i^3) and the soils of the southern parts are from flood plain deposits consisting of silt, clay, and sand with salt (Q^{scs}) and marsh deposits consisting of silt and clay with salt (Q^{sc1}) (Figure 1a). The cultivated lands in the northern areas are irrigated with quality water, while the irrigated lands in the southern areas are irrigated with saline water, and this has probably caused the salinization of the soils in these areas. The study area comprises several landforms, including alluvial fans, bajada, alluvial plains, pediment, and clay flats (playa) (Figure 2 and Table 1). The major geof ormation processes, especially in the late Tertiary and early Quaternary periods, are erosional and depositional processes. According to Soil Taxonomy, the soil temperature and moisture regimes are Hyperthermic and Aridic-Ustic, respectively. Moreover, soils in this region are predominantly classified under three sub-great groups: Ustic Haplocalcids, Ustic Haplocambids, and Ustic Torriorthents [46].

2.2. Data Collection and Soil Sample Analyses

A total of 300 surface soil samples (0–30 cm) were collected using the conditional Latin hypercube sampling (cLHS) technique [47], which was based on a wide variety of environmental covariates (RS indices, topographic attributes, geology and geomorphology maps) (Figure 1). The soil samples were prepared based on the standard method, and the electrical conductivity of the saturated paste extract (ECe) was determined using a conductivity meter [48,49].

The electromagnetic induction device (EMI, Geonics EM38) was used to determine the ECa at the sampled locations. The instrument is capable of measuring ECa in two modes: horizontal (ECah) and vertical (ECav), with effective depths of 0.75 and 1.5 m, respectively [50]. The EMI readings were performed in July 2019, when soil moisture was minimal, to minimize the soil moisture variation effects. Although diurnal temperature variation has little effect on ECa [51], the measurements were taken midmorning to coincide with soil surface that might be a daily average temperature.

Figure 1. Study area location. (a) Lithological map in the study area, and (b) Sentinel-2A image and location of sampling sites in the study area and demonstration of the landscape of the sampling sites (c–e). Geological formation (a): OM^{las} : limestone thin-bedded to massive feature forming (ASMARI.F), R_{ds}^{ad} : anhydrite, dolomite, shale, and marl, Q_i^3 : silty, sandy, and clay flat, Q^{ap} : alluvial, colluvial, and proluvial deposits of major channels and stream, Q^8 : poorly consolidated alluvial–proluvial deposits in young terraces, consisting of subrounded gravels and sand, silt, and clay, Q^{sc1} : marsh deposits consisting of silt and clay with salt, Q^{scs} : flood plain deposits consisting of silt, clay, and sand with salt.

Figure 2. Geomorphology map of the study area. Codes that refer to geomorphic surfaces are presented in Table 1.

Table 1. Geomorphic units related to the map (Figure 2) for the study area.

Landscape	Landform	Lithology	Geomorphological Surface	Code
Mountain	Eroded rock outcrop	OM^1_{as}	Rock surfaces	Mo111
		R^{ad}_{ds}	Rock surfaces	Mo121
Hill	Eroded outcrop	R^{ad}_{ds}	Rock outcrops with braided stream	Hi111
Piedmont	Alluvial fan	Q^3_t	Active fan, upper section, high slope	Pi111
			Active fan, lower section, low slope	Pi112
		Q^{ap}	Active fan, lower section, low slope	Pi121
	Bajada	Q^3_i	Upper section, high slope, dense drainage system	Pi211
			Lower section, low slope	Pi212
	Pediment	Q^3_t	High slope, rocky	Pi311
			Low slope, cultivated	Pi312
		Q^8	High slope, rocky	Pi321
			Low slope, cultivated	Pi322
		Q^{sc1}	Low slope, cultivated	Pi331
		Q^{scs}	High slope, rocky	Pi341
			Low slope, cultivated	Pi342
	Alluvial plain	Q^{ap}	Cultivated, saline	Pi411
			Cultivated	Pi412
		Q^8	Cultivated	Pi421
		Q^{scs}	Cultivated	Pi431
River	River sediments	Q^{ap}	Channel sediments	Ri111
Playa	Clay flat	Q^3_t	Cultivated clay flat	PI111
		Q^{sc1}	Salty and cultivated	PI121
		Q^{scs}	Gypsic, salty, and wetness	PI131
			Soft clay flat, salty, and cultivated	PI132
			Gypsic, salty with low drainage	PI133

Moreover, the elemental concentrations of the dry-sifted samples were determined using pXRF equipment [38]. The instrument was operated in Soil Mode, which is capable of detecting various elements. Scanning for Soil Mode was performed at a rate of 30 s per beam. Each sample was scanned once in Soil Mode; however, each scan was an average of internal scans performed at 1 s intervals. The pXRF output generated a geochemical profile of elemental concentrations and raw pXRF spectra for each of the three beams. Considering both the precision level of the XRF and the elemental ranges of the samples used in Soil Mode, only the contents of four elements (K: potassium; Ca: calcium; S: sulfur; Cl: chlorine) were used in this study because these elements are the main constituents of soluble salts in soil (e.g., various combinations of Mg^{2+} , Na^+ , K^+ , Ca^{2+} , Cl^- , SO_4^{2-} , CO_3^{2-} , and HCO_3^-) [52].

2.3. Collection of Auxiliary Data

The environmental covariates employed in this study included four auxiliary covariates comprising RS indices, PS data, topographic covariates taken from a digital elevation model (DEM), and geology and geomorphology maps (Table 2).

Table 2. Covariates used for spatial prediction of soil salinity.

Auxiliary Data	Covariate	Definition	Reference/Source
	SySI bands	Synthetic Soil Image	[53]
	Sentinel-2A bands		
	Salinity Index 1 (SI)	$\sqrt{B2 \times B4}$	[54,55]
	Salinity index 2 (SI1)	$\sqrt{B3 \times B4}$	[54,55]
	Salinity Index 3 (SI2)	$\sqrt{B3^2 + B4^2 + B8A^2}$	[54,55]
	Salinity Index 4 (SI3)	$\sqrt{B3^2 + B4^2}$	[54,55]
	Salinity Index 5 (S)	$B4/B8A$	[56]

Table 2. Cont.

Auxiliary Data	Covariate	Definition	Reference/Source
	Salinity Index (S1)	$B2/B4$	[57]
	Salinity Index (S2)	$(B2 - B4)/(B2 + B4)$	[57]
	Salinity Index (S3)	$(B3 \times B4)/B2$	[57]
	Salinity Index (S5)	$(B2 \times B4)/B3$	[57]
	Salinity Index (S6)	$(B4 \times A8A)/B3$	[57]
	Salinity Index-T (SI-T)	$(B4/B8A)/100$	[57]
	Brightness Index (BI)	$\sqrt{B4^2 + B8A^2}$	[57]
	Normalized Difference Salinity Index (NDSI)	$(B4 - B8A)/(B4 + B8A)$	[57]
	Normalized Difference Vegetation Index (NDVI)	$(B8A - B4)/(B8A + B4)$	[58]
	Enhanced Vegetation Index (EVI)	$\frac{2.5 \times (B8A - B4)}{(B8A + 6 \times B4 - 7.5 \times B2 + 1)}$	[59]
	Normalized Difference Vegetation Index red-edge 1 (NDVire1)	$(B8A - B5)/(B8A + B5)$	[59]
	Normalized Difference Vegetation Index red-edge 2 (NDVire2)	$(B8A - B6)/(B5 + B6)$	[59]
	Ratio Vegetation Index (RVI)	$B8A/B4$	[60]
	Renormalized Difference Vegetation Index (RDVI)	$(B8A - B4)/(\sqrt{B8A + B4})$	[27]
Proximal sensing data	Apparent Electrical Conductivity (ECa readings (ECa _h and ECa _v)) Portable X-Ray Fluorescence (pXRF)	Calculated the ECa of soil volume down to 1.5 m elemental concentration (K, Ca, Cl and S)	Geonics Ltd. EM38
Topographic attributes	Elevation (m) Analytical Hillshading Aspect Channel Network Base Level Cross-Sectional Curvature Convergence Index Closed Depressions Flow Accumulation General Curvature Longitudinal Curvature LS Factor Multi-resolution of Ridge Top Flatness Index Multi-resolution Valley Bottom Flatness Index Plan Curvature Profile Curvature Relative Slope Position Slope Topographic Wetness Index Total Curvature Valley Depth Vertical Distance to Channel Network	El AH Aspect CNBL CSCu CI CD FA GCu LCu LSF MRRTF MRVBF PICu PrCu RSP Slope TWI TCu Val_Dep VDCN	SAGA GIS
Geology Geomorphology	Geology map Geomorphology map	Geomorphology surfaces	[61]

2.3.1. Remote Sensing and Selection of Spectral Index

The RS image data used in this investigation were derived from Sentinel-2A. The satellite images in this study were obtained from the website [62] (<https://scihub.copernicus.eu/dhus/#/home>, accessed on 23 November 2021) of the European Space Agency [63] (<https://www.esa.int/ESA>, accessed on 23 November 2021), which was basically synchronous with the sampling time, and there was no cloud in the study area. Furthermore, we used the multi-temporal bare soil technique from the Sentinel-2A satellite. Multi-temporal bare soil images known as SySI (Synthetic Soil Image) were produced from the Sentinel-2A images using the Geospatial Soil Sensing System method (GEOS3) [64]. Images from the Sentinel-2A satellite, at Level-1C (Top of Atmosphere reflectance, TOA), were obtained from the Copernicus website [62] (<https://scihub.copernicus.eu/dhus/#/home>, accessed on 23 November 2021), from 2015 to 2020. These needed to be corrected from TOA to BOA (Bottom of Atmosphere); thus, we used the Sen2Cor plugin for correction [65]. These Level-2A (BOA) images were processed using the statistical software R [66]. Sentinel-2 MSI images have a spatial resolution of 10 to 60 m, but we used spectral bands with 10 and 20 m pixel sizes. The near-infrared (NIR) bands (band 8A) were available in 10 m pixel size and were resampled to 20 m using the *resample* function and the *bilinear* method in R software to ensure the same spatial extent of all spectral bands [66].

The GEOS3 method consists of (1) obtaining the images, (2) masking pixels that were non-bare soil, and (3) calculating the median reflectance of the masked images. After obtaining the images, spectral indices such as *NBR2* (Normalized Burn Ratio 2) and *NDVI* (Normalized Difference Vegetation Index) were calculated and used to mask the images. Following the GEOS3 method, each of the images obtained was masked from two spectral indices. The *NDVI* was used to mask vegetation (Equation (1)), both natural and planted. For this purpose, all pixels that were not in the range of -0.15 to 0.25 were discarded, maintaining only those that had a soil response. Then *NBR2* was used to mask straw (Equation (2)), with an interval between -0.15 and 0.15 . Subsequently, cloud or cloud shadow was also masked to prevent them from interfering with the final image. Then, using the median between the pixels of all satellite images, SySI was calculated. The SySI was composed of nine surface reflectance data from the regions visible, near-infrared, and shortwave infrared (Vis-NIR-SWIR) that included bands Blue, Green, Red, Red Edge₁, Red Edge₂, Red Edge₃, Red Edge₄, *SWIR*₁, and *SWIR*₂ (Figure 3), which were later used as soil salinity predictors.

$$NDVI = \frac{NIR - RED}{NIR + RED} \quad (1)$$

$$NBR2 = \frac{SWIR_1 - SWIR_2}{SWIR_1 + SWIR_2} \quad (2)$$

Since the spectral indices are an effective way to detect soil salinity in arid and semi-arid regions [67,68], in this study, we employed commonly used spectral indices, including salinity index and vegetation index, to generate a strong combination for the creation of detection model (Table 2). We calculated vegetation indices using Sentinel-2A satellite images and salinity indices using bare soil images (SySI) and Sentinel-2A satellite images.

2.3.2. Proximal Sensing Data

In this study, the data obtained from EMI (EC_{ah} and EC_{av}) and pXRF (K, Ca, S, and Cl) were used as auxiliary covariates to improve the accuracy of soil salinity prediction. The variables acquired by EC_a and pXRF were spatialized for the whole study region based on the definition of the optimal modeling approach. To do so, the EC_a and pXRF variables were spatialized using the ordinary kriging method in ArcMap 10.5, allowing them to be used for mapping later.

Figure 3. Multi-temporal bare soil image from Sentinel-2A satellite, Synthetic Soil Image (SySI).

2.3.3. Topographic Attributes

In DSM studies, topographic attributes are the most widely used surface parameters [4,68]. Salt distribution and redistribution are influenced by terrain conditions [68]. Therefore, in this study, the effect of topographic attributes on soil salinity prediction was investigated. The Aster GDEM database was used to download a DEM with a cell size of 20 m [69] to obtain the topographic attributes. The terrain attributes obtained from DEM that were derived by SAGA software are presented in Table 2.

2.3.4. Geology and Geomorphology Maps

Other valuable sources of information for assessing soil properties are geology and geomorphology maps that present soil parent material and soil genesis, and other soil-forming factors, especially in arid regions [12,68]. The geomorphic units were determined using a nested hierarchy described by Toomanian et al. [61]. For the purpose of the breakdown of the intricacy of various landscapes, a four-level geomorphic hierarchy was used in this method: landscapes, landforms, lithology, and geomorphology, and ultimately, 25 geomorphic units were mapped (Figure 2 and Table 1).

2.4. Preprocessing and Feature Selection

When a model has a high number of predictors, improving its performance and general capabilities requires an exhaustive search of all possible subsets to choose the best predictors [70,71]. Furthermore, several of the models in the *caret* package do not need all the predictors, and using feature selection for these models would be more efficient [72].

Three scenarios were investigated to determine the capability of the combined RS and PS data, topographic attributes, geology map, and geomorphology map to estimate ECe, including:

Scenario (1): Using only 9 SySI bands and 13 salinity indices derived from SySI; Scenario (2): Using RS data (10 Sentinel multispectral bands, 13 salinity indices, and 6 vegetation indices), PS data (ECa and elemental concentration by pXRF), topographic attributes (21 attributes extracted from DEM), and geology and geomorphology maps; and Scenario (3): Using total variables including RS data (10 Sentinel multispectral bands, 13 salinity indices, and 6 vegetation indices), 9 SySI bands and 13 salinity indices derived from SySI, PS data (ECa and elemental concentration by pXRF), topographic attributes (21 attributes extracted from DEM), and geology and geomorphology maps to estimate ECe.

2.5. Modeling Approaches

For modeling, the following preprocessing was applied to the data. Because the ECe data had a log-normal distribution, it was log-transformed before being preprocessed and modeled. First, the variance inflation factor (VIF) was calculated for each covariate to check the impact of multicollinearity in each MLR model and covariates with VIF >10 were removed from the datasets [73]. In the next step, the Boruta method was applied to select the most important covariates with the target covariate (ECe). Then, a linear technique represented partial least squares regression (PLSR), and three non-linear techniques, artificial neural networks (ANN), random forest (RF), and support vector machines (SVM), were used for modeling. In addition, k-nearest neighbors (kNN) was considered a non-parametric algorithm necessary for accurately modeling non-linear data and interpolating point source soil data across the landscape [74]. Then, the final ensemble model was composed of five individual predictions (one for each calibration technique), which were weighted averaged [19]. All feature selections and modeling were performed using the “caret” and “caretEnsemble” packages in R 3.5.2 [66].

The Pearson correlation coefficients were calculated between soil salinity from the topsoil (0–30 cm) and environmental covariates. The statistical analysis was performed in the R environment [66], using the package *corrplot* [75].

2.6. Assessment of Model Performance

The prediction performance of models was assessed using 10-fold cross-validation [76]. Cross-validation provides a structure for creating several train/test splits in the dataset and guaranteeing that each data point is in the test set at least once. The advantage of this method is that it performs reliably and is unbiased on smaller datasets. To compare the modeling performance and determine the optimal model, the coefficient of determination (R^2), root mean square error (RMSE), mean absolute error (MAE), and normalized root mean square error (nRMSE) were calculated. RMSE means show how close the predicted values are to the observed values, and the coefficient of determination (R^2) shows the proportion of the variance in the target covariate that the model explains.

$$R^2 = 1 - \frac{\sum_{i=1}^n (Z * (X_i) - Z(X_i))^2}{\sum_{i=1}^n (Z(X_i) - \bar{Z}(X))^2} \quad (3)$$

$$RMSE = \left[\frac{\sum_{i=1}^N [Z(X_i) - Z * (X_i)]^2}{N} \right]^{1/2} \quad (4)$$

$$MAE = \frac{1}{N} \sum_{i=1}^N [|Z(X_i) - Z * (X_i)|] \quad (5)$$

$$nRMSE = \frac{RMSE}{\bar{Z}(X)} \times 100 \quad (6)$$

where $Z(X_i)$ and $Z*(X_i)$ are the observed and predicted values, respectively, and $\bar{Z}(X)$ is the average of observed values, and N is the number of measurements.

3. Results

3.1. Descriptive Statistics of Field Measurements (ECe, ECa, and pXRF)

Table 3 presents the descriptive statistics of ECe, EM38 readings, and concentrations of elements measured with pXRF. The ECe showed a broad range from 0.48 to 73.92 dS m^{−1}, while the log-transformed ECe values ranged from −0.31 to 1.87 log₁₀ dS m^{−1} (Table 3). These values were used as the dependent covariate for modeling (Table 4). The ECav ranged between 7 and 431 mS m^{−1} with a mean value of 45.92 mS m^{−1}, whereas the ECah varied from 3 to 198 mS m^{−1} with an average of 26.64 mS m^{−1}. The coefficients of variation (CV) for ECe, ECav, and ECah were 150.43, 128.25, and 117.90%, respectively (Table 3).

Table 3. Descriptive statistics of soil salinity (dS m^{-1}), log-normal soil salinity (dS m^{-1}), electromagnetic induction readings, and concentrations of elements measured with pXRF in all studied surface soil samples ($N = 300$).

Soil Properties	Unit	Min	Max	Mean	StDev	CV%	Skew.	Kurt.
ECe	dSm^{-1}	0.48	73.92	7.31	10.99	150.43	3.19	12.37
Log_{10} ECe	dSm^{-1}	−0.31	1.87	0.52	0.54	102.23	0.39	−0.86
ECav	mSm^{-1}	7	431	45.92	58.89	128.25	3.61	16.81
ECah	mSm^{-1}	3	198	26.64	31.41	117.90	2.58	8.23
K	mg kg^{-1}	914	18,410	13,485	2540.80	18.84	−1.83	5.27
Ca	mg kg^{-1}	116,000	454,000	285,170	53,118.13	18.62	0.47	0.78
S	mg kg^{-1}	0	329,000	9816	36,159.78	368.34	5.88	38.84
Cl	mg kg^{-1}	306	10,944	1265.80	1334.51	105.42	4.03	19.01

ECe: electrical conductivity; Log_{10} : logarithm base 10, ECav: apparent electrical conductivity (vertical mode); ECah: apparent electrical conductivity (horizontal mode); K: potassium; Ca: calcium; S: sulfur; Cl: chlorine; Min: minimum; Max: maximum; StDev: standard deviation; CV: coefficient of variation; Skew: skewness; Kurt: kurtosis.

Table 4. Validation criteria for prediction of the soil electrical conductivity (ECe ; dS m^{-1}) of all models. The values that are bolded indicate the results with the highest accuracy.

Model	Scenario (1)				Scenario (2)				Scenario (3)			
	RMSE	R^2	MAE	nRMSE	RMSE	R^2	MAE	nRMSE	RMSE	R^2	MAE	nRMSE
kNN	3.38 ± 1.10	0.06 ± 0.07	2.79 ± 1.08	46.21	2.86 ± 1.11	0.29 ± 0.12	2.38 ± 1.09	39.13	2.92 ± 1.11	0.26 ± 0.10	2.41 ± 1.09	39.97
ANN	3.07 ± 1.12	0.20 ± 0.14	2.55 ± 1.10	42.00	2.89 ± 1.13	0.28 ± 0.15	2.43 ± 1.12	39.59	2.99 ± 1.13	0.25 ± 0.15	2.49 ± 1.13	40.93
PLS	3.13 ± 1.12	0.17 ± 0.12	2.59 ± 1.09	42.89	2.81 ± 1.12	0.32 ± 0.15	2.36 ± 1.09	38.45	2.93 ± 1.12	0.27 ± 0.14	2.41 ± 1.10	40.06
RF	3.02 ± 1.13	0.22 ± 0.11	2.40 ± 1.10	41.39	2.50 ± 1.10	0.47 ± 0.11	2.12 ± 1.019	34.16	2.49 ± 1.11	0.48 ± 0.13	2.10 ± 1.09	34.11
SVM	2.97 ± 1.14	0.26 ± 0.12	2.33 ± 1.11	40.59	2.64 ± 1.16	0.44 ± 0.12	2.15 ± 1.15	36.09	2.63 ± 1.16	0.45 ± 0.13	2.15 ± 1.15	35.94
Ensemble	2.22	0.58	1.79	30.45	1.89	0.73	1.56	25.92	1.76	0.79	1.47	24.12
RI (%) *	33.28	120.95	30.56	33.28	31.82	56.82	35.42	31.82	41.40	66.71	42.95	41.40

Scenario (1): modeling with SySI bands and salinity indices derived from it; Scenario (2): modeling with RS data, PS data, topographic attributes, geology and geomorphology maps; and Scenario (3): modeling with a combination of Scenarios (1) and (2). * RI: relative improvement of RMSE, R^2 , MAE, and nRMSE of ensemble method compared with the most accurate prediction for the soil electrical conductivity (ECe ; dS m^{-1}).

According to the soil salinity classification, the U.S. Salinity Laboratory Staff [52], 11% of the soil samples were strongly saline (≥ 16 dS m^{-1}), 18% moderately ($8\text{--}16$ dS m^{-1}), 13% slightly ($4\text{--}8$ dS m^{-1}), 15% very slightly ($2\text{--}4$ dS m^{-1}), and 43% non-saline ($0\text{--}2$ dS m^{-1}).

The results showed that 42% of samples had an ECe of more than 4 dS m^{-1} , indicating salt-affected soils. The pXRF instrument was used to measure K, Ca, S, and C elements and these were applied for soil salinity modeling. CV for K, Ca, S, and Cl contents were 18.84, 18.62, 368.34, and 105.42%, respectively (Table 3). Among the measured elements, the highest mean ($285,170$ mg Kg^{-1}) was related to Ca. This is probably due to the accumulation of calcium carbonate in the soils of this region (Table 3). In the arid and semi-arid regions, calcium carbonates accumulate in the top-surface due to high temperatures and low precipitation amounts [77].

3.2. Correlations between ECe and Environmental Covariates

Since the present study aimed to investigate the effects of using auxiliary covariates independently and in combination on soil salinity as a target covariate, the VIF procedure was used to reduce variables. The covariate reduction has been used to reduce errors in predictions [78] through the removal of potentially irrelevant predictor covariates. Since weak learners produce weak outliers, the process progressively increases the prediction accuracy by reducing the chance of obtaining outliers [79]. A total of 51 covariates were derived from the RS data, and 7 covariates were retained. Of the six covariates from the PS data, five remained, while out of 21 topographic attributes extracted from DEM, only four covariates were included in the final environmental dataset. Finally, Pearson's correlation analysis was performed, and a correlogram was constructed to investigate the sensitivity of the remaining environmental factors to soil salinity (Figure 4). Soil salinity showed a high correlation with the PS data, relatively weak correlation with topographic attributes, and low correlation with the RS data (Figure 4). Therefore, PS data could play an important role in prediction and improving the accuracy of ECe. PS data including Cl, ECav, and ECah showed a positive correlation, while K and Ca negatively correlated with soil salinity (Figure 4).

Figure 4. Pearson's correlation coefficients between soil salinity and the selected covariates after the VIF procedure and covariate selection (Boruta algorithm) in various datasets ($N = 300$). The environmental covariates are presented in Table 2.

Among the four topographic attributes, the correlation between MRVBF and ECe was positive and high; however, CNBL, Val_Dep, RSP, and ECe showed a negative correlation with ECe. The highest correlation was related to CNBL, followed by MRVBF, Val_Dep, and RSP (Figure 4). The results showed a weak correlation between the covariates derived from RS, including spectral bands, vegetation indices, salinity indices, and ECe (Figure 4).

3.3. Covariate Importance

Figure 5 shows the measured importance of the examined predictor covariates taken from the Boruta algorithm for each scenario. The results showed that salinity indices were obtained from SySI, including S2.SySI, S1.SySI, and NDSI.SySI, and are the most important covariates for predicting ECe in Scenario (1) (Figure 5a). In Scenario (2), the PS data (ECah, ECav, Ca, Cl, and K) with 56% of total relative importance were the main covariates for predicting ECe content. Just afterward came the topographic attributes (CNBL and Val_Dep) with 22%, RS data (NDVIre2) with 12%, and geology and geomorphology maps with 10% as important covariates for predicting soil salinity (Figure 5b). In Scenario (3), the highest importance was related to the PS data (ECav, ECah, Ca, Cl, and K) with 40% of the total relative importance, followed by topographic attributes (CNBL, Val_Dep, MRVBF, and RSP) with 23%, salinity indices obtained from SySI (S2.SySI, S1.SySI, and NDSI.SySI) with 17%, RS data (EVI and Sentinel_B07) with 12%, and geology and geomorphology maps with 8% were the most important covariates for predicting ECe (Figure 5c).

Figure 5. Relative importance of environmental covariates (%) for predicting ECe content in various datasets for the best prediction models. (a) Scenario (1): modeling with SySI bands and salinity indices derived from it; (b) Scenario (2): modeling with RS data, PS data, topographic attributes, geology and geomorphology maps; and (c) Scenario (3): modeling with a combination of Scenarios (1) and (2). The environmental covariates are presented in Table 2.

3.4. Modeling Performance and Evaluation

The performance of models (i.e., kNN, ANN, PLS, RF, SVM, and ensemble model) for predicting ECe content in each scenario was compared based on R^2 , MAE, RMSE, and $nRMSE$ indices (Table 4). The best prediction accuracy was obtained using the SVM model in Scenario (1), while the RF model outperformed in the others ((2) and (3)) (Table 4). However, the comparison between all scenarios showed that the best prediction accuracy

is obtained for the RF model in Scenario (3) ($R^2 = 0.48$ and $RMSE = 2.49$), followed by Scenario (2) for the RF model ($R^2 = 0.47$ and $RMSE = 2.50$), and then Scenario (1) for the SVM model ($R^2 = 0.26$ and $RMSE = 2.97$). Comparison of three scenarios showed that there was a difference between the models developed with Scenarios (1) and (2) and Scenarios (1) and (3). However, there was a little difference between the developed models with Scenarios (2) and (3). In ECe modeling, the difference in the value of R^2 for the best model was 0.21 in Scenarios (1) and (2) and 0.22 in Scenarios (1) and (3), but the R^2 value differed 0.01 for the best model in Scenarios (2) and (3) (Figure 5 and Table 4). We employed the ensemble modeling technique to see whether we could enhance the prediction of soil salinity (Table 4). Results showed that the ensemble model had the best performance in Scenario (3) with $R^2 = 0.79$ and $RMSE = 1.76$, followed by Scenario (2) with $R^2 = 0.73$ and $RMSE = 1.89$, and then Scenario (1) with $R^2 = 0.58$ and $RMSE = 2.22$ (Table 4). This indicates that the ensemble modeling approach produced more accurate and dependable predictive soil salinity results than the individual models (Table 4). Relative improvement (RI%) indicated that the R^2 index in the ensemble model improved compared with the most accurate prediction for Scenarios (1), (2), and (3) with 120.95, 56.82, and 66.71%, respectively (Table 4).

Results indicated that PS data and topographic attributes are important in predicting ECe, and better results were obtained when all auxiliary covariates (RS and PS data, salinity indices obtained from SySI, topographic attributes, and geology and geomorphology maps) for salinity prediction were combined (Table 4). Moreover, the results demonstrated that the selection of environmental covariates influences prediction accuracy (Table 4). Environmental covariates derived from SySI had a low correlation with ECe, which is possibly the reason for the low accuracy estimation in Scenario (1) (Figure 4 and Table 4).

3.5. Spatial Distribution of Soil Salinity

Figure 6 shows the spatial distribution of ECe using the best performance model for three scenarios. The spatial patterns of ECe produced for the three scenarios corresponded with the distribution of known topographic features in the region. The prediction maps of ECe by the three scenarios indicated that ECe tended to increase from northwestern to south and southeastern regions. The regions with high ECe were located in low elevations and playa, where halophyte plant *Suaeda aegyptiaca* grows. The regions with low ECe were located in the higher elevations with steeper slopes and alluvial fans (Figures 1 and 6). A large amount of salt is likely discharged from the middle and upper parts of the alluvial fans [12]. The discharged salts flow to the surrounding area at a low altitude in central and southern areas (Figures 1 and 6). Generally, this is because the higher sections of the area have a sandy texture and low salt absorbability. There occurs leaching and discharge of salts to the lower parts, which have a clay texture and poor drainage (Figure 6). The spatial patterns of ECe also corresponded with the lithological map so that the soil of the southern parts generally has a geological formation Q^{scs} and Q^{sc1} , which contains salt (Figures 1a and 6). As shown in Figure 6, three scenarios predicted low ECe values appropriately; however, the high ECe values are relatively underestimated. The minimum predicted ECe by Scenario (1) is 0.660 dS m^{-1} , and the maximum is 11.089 dS m^{-1} (Figure 6a), while the maximum ECe by Scenarios (2) and (3) are 9.997 dS m^{-1} and 22.42 dS m^{-1} , respectively (Figure 6b,c).

Figure 6. Spatial prediction maps of soil salinity (dS m^{-1}) using different datasets for the best prediction models. (a) Scenario (1): modeling with SySI bands and salinity indices derived from it; (b) Scenario (2): modeling with RS data, PS data, topographic attributes, geology and geomorphology maps; and (c) Scenario (3): modeling with a combination of Scenarios (1) and (2).

4. Discussion

In the study, ground observations and environmental covariates were integrated to map soil salinity. This property has a wide range in the study area. This is likely due to

the fact that landscape position, soil type, parent material, and other variables influence soil salinity variations [80]. Additionally, soil salinity changes quickly over short distances due to topography and other variables [81]. Therefore, we used RS and PS techniques to predict soil salinity as the cost and time-efficient approach. In this study, we obtained a lower CV for EC_{ah} and EC_{av} values than EC_e, which was consistent with the results of Taghizadeh-Mehrjardi et al. [4]. They stated this is because the instrument measures EC_a in a larger soil volume, while smaller soil samples were measured for EC_e.

In a study conducted in Texas, the USA, Aldabaa et al. [18] predicted soil salinity by combining RS data and content of soil elements measured by pXRF. They reported that S and Cl had the highest CV values among the elements, which indicated outliers for these two elements. Similarly, among the elements measured by pXRF, S and Cl had the highest CV in this study.

The positive correlation between soil salinity and Cl indicates that the origin of salinity in the region is probably salts that contain Cl (halite). Aldabaa et al. [18] also reported a high correlation between log₁₀ EC with S (0.78) and Cl (0.60). The authors stated that the high correlation indicated the origin of salinity when salts contain SO₄^{2−} (gypsum) and Cl[−] (halite). They also reviewed the results of energy-dispersive X-ray spectroscopy and found that S, Na, Mg, O, Cl, K, Al, and Ca were prevalent elements in high salinity samples (especially Cl and S). On the other hand, they found that Ca, Mg, Si, K, O, and Al are prevalent elements in non-saline samples. This finding is consistent with the result of the negative correlation between EC_e and Ca and K in our study.

Although the study area comprises several land uses, geological formations, and geomorphic surfaces (Figures 1 and 4), it could be concluded that the relatively weak correlations between topographic attributes and soil salinity are probably because the study area has a relatively flat topographic system in most of the area [82]. In addition, due to the flatness in the middle and southern parts of the area, surface runoff due to precipitation was limited, preventing salts' redistribution [68,83].

Peng et al. [68], working in southern Xinjiang Province, China, reported that CNBL and RSP variables, among the topographic attributes, have a significant negative correlation with salinity, and this result was consistent with our finding. According to previous research [84,85], some topography indices (elevation, RSP, Val_Dep, and CNBL) have a strong relationship with EC and significantly affect other soil characteristics. In a study in Dongying City, Shandong Province, China, Yang et al. [82] obtained a high correlation between elevation and total salt content. They attributed this to the effect of elevation on groundwater level, which significantly impacts water and salt migration. Moreover, they have reported a very weak correlation between profile curvature, plan curvature, and TWI with total salt due to the flatness of the region. In agreement with our findings, Akramkhanov et al. [83], in a study in Khorezm Province, Uzbekistan, reported that most terrain attributes had a low correlation with topsoil properties and bulk salinity, as their study area was rather flat.

Different spectral behaviors affected by variable rates of soil salinity are the basis for monitoring surface soil salinity using RS data [29]. In different works, spectral bands and a salinity index [86–88] have been directly used as a vegetation index [56,84,88] with an indirect approach. The low correlation between satellite data and soil salinity is probably due to the fact that a small part of the study area has a salinity of more than 8 dS m^{−1}, and salinity is not visible at the soil surface (Figure 4). Moreover, in some parts of the area, the white color on the soil surface is due to the presence of gypsum or surface gravel, which causes errors in salinity monitoring using satellite data. Zeraatpisheh et al. [89] reported that when the study area has low vegetation indices (e.g., NDVI lower than 0.3), there is no or very low correlation between RS covariates and soil organic carbon content.

The corresponding reflectance characteristics of the eight representative soil samples with different EC_e for the SySI and Sentinel-2A band showed that samples with EC_e of 66.02 and 33.21 dS m^{−1} attained a higher reflectance than the other samples in the SySI band. In contrast, in the Sentinel-2A band, soil samples with an EC_e 66.02 dS m^{−1} showed

the highest reflectance (Figure 7a,b). The reflectance curve of the soil samples in the SySI band with an ECe ranging from 0.53 to 16.38 dS m^{-1} was more concentrated, and the reflectance in the nine wavebands was low (Figure 7). In this study, the soil samples with the lowest and highest ECe did not correspond to the lowest and highest reflectance curves, respectively, which should be closely related to the salt composition, soil moisture content [90,91], and other soil properties such as gypsum, carbonate, soil organic carbon, and soil texture. Wang et al. [5] stated that areas covered by a white salt crust have a large amount of salt. They also indicated that the spectral reflectance of the soil samples does not necessarily increase with increasing soil salinity in each band of the Sentinel-2 MSI data. This fact makes it difficult to map and monitor the soil surface salinity using multispectral bands and their derived indices. It can also be observed that spectral behavior has a trend where the spectra increase from lower to higher ECe (from visible to SWIR_2), forming an angle. In both cases, the trend of SySI and Sentinel maintained the higher ECe with greater reflectance and increased type.

Figure 7. Reflectance of the soil samples with different salinity levels in the (a) SySI bands and (b) Sentinel-2A spectral bands.

The results indicated that the RF and SVM models had a higher performance in predicting soil salinity among the models investigated (Table 4). These higher accuracies are due to the ability of the algorithms to handle the non-linear relationships, which are typically observed between soil salinity, ground observations, and environmental covariates. Although the differences between the modeling performance in Scenarios (2) and (3) are not significant, the most important factors affecting model performance are mainly sample density and input variables. Since the number of samples in this study was consistent in two scenarios, different environmental variables in the two scenarios induced different performances [13]. In a study in Aksu Province, China, Wang et al. [5] indicated that the SVM soil EC estimation model had higher performance and accuracy than soil EC estimation models created with ANN and RF models. In a study conducted in southern Xinjiang, China, Wang et al. [79] found that RF was the best algorithm for predicting soil salinity in arid regions.

The modeling results showed that the ensemble soil ECe estimation model performed better than the individual approaches (Table 4). This is because the polynomial ensemble model can combine the strengths of individual ones [26]. The ensemble model improved the validation indicators positively compared to the best individual model in all scenarios (Table 4). According to Heung et al. [92], ensemble learning is a strategy for improving the consistency of results in soil surveys with complicated relationships between variables.

In many previous studies, regions with vegetation coverage were directly identified as non- or slightly salinized [93,94]. However, in our study, areas with high salinity also have vegetation because these areas are generally irrigated with saltwater, and salt-tolerant plants such as barley, wheat, and dates are grown. Because of differences in topography, vegetation kinds, and geographic location, the soil salinity under vegetation cover varied from non-saline to heavily saline soil [95,96].

Our results showed that the covariates obtained from PS are more important and practical predictors of soil salinity than RS. These results were consistent with previous studies [18,36]. The data also showed that EC_{ah} and EC_{av} were more important among the PS data (Figure 5), which is confirmed by the results of Taghizadeh-Mehrjardi et al. [4]. These authors reported that EC_{av} was the most important covariate for predicting EC_e in surface soils.

5. Conclusions

The present study was conducted to investigate the spatial variation of soil salinity using multiple machine learnings and environmental covariates in an arid region in Iran. Since EMI is sensitive to soil salinity and moisture, and pXRF directly measures constituent soil elements that play a role in soil salinity (Cl), PS showed a higher correlation than RS and topographic attributes. The low correlation between satellite data and soil salinity is probably because salt is not visible at the soil surface. Thus, our results showed that covariates obtained from PS are more important than RS covariates and could be more precise to predict soil salinity. The results showed that the ensemble model was generally successful, as it produced a more accurate prediction for soil salinity than individual ones. The ensemble modeling method positively improved the validation indicators more than the best individual model in all scenarios.

We propose that the PS, RS data, and topographic attributes be merged for optimal soil salinity prediction because these data types are inexpensive, easy, and rapid to obtain and can be used for soil salinity management. The results of this study showed that the combination of PS and RS data with topographic attributes could be successfully used to monitor and map other basic soil properties such as textural constituents, soil pH, carbonate, gypsum, and soil organic carbon in the future. In doing so, researchers will be able to achieve results that are comparable to lab-derived data while spending less time and making less attempts than traditional laboratory determinations.

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