

Proceeding paper

Comparing the Potential of Multispectral and SAR Models in Estimating Soil Salinity [†]

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Abstract: The increasing environmental impact of salinity has significantly affected the global community's needs. Considerable number of empirical and semi-empirical soil salinity indices have been extensively studied in various studies utilizing data from multispectral and SAR sensors. Since the performance of such models is contingent upon multiple environmental parameters, it is imperative to understand their applicability across a range of environmental conditions. This knowledge will enhance the well-being of farmers, their livelihoods, and the overall ecosystem. This study investigates and compares the effectiveness of different salinity models in estimating soil salinity in the study region using Sentinel-1, Sentinel-2, and Landsat 8 OLI data products. Firstly, the potential of various soil salinity indices, developed by analyzing different combinations of visible and infrared bands from Sentinel 2A, along with a modified salinity index (MSI) developed for Landsat data, was examined. Further, the study evaluated the performance of dielectric simulations of SAR (Synthetic Aperture RADAR) data, namely DSDM-SS (Density Space Dielectric Model for soil salinity) and Hallikainen models. Based on the comparison with in-situ data, it was observed that the Hallikainen model performed well in irrigated conditions, while the modified salinity index (MSI) showed promising results in dry conditions.

Keywords: Soil Salinity; Appraisal; Multispectral indices; SAR; Dielectric Models

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1. Introduction

Soil salinization is a process by which the salt concentration in the soil increases to levels that become harmful to plants and the overall ecosystem [1]. It is a significant environmental issue that can have detrimental effects on agriculture, ecosystems, and human activities [2]. Soil salinity results in prolonged clogging of soil pores which makes difficulty for plants in absorbing the moisture content and causing soil moisture stress especially in the root zone of the plants [3]. Scientists and agricultural experts continually research and monitor soil salinity levels to better understand its causes and effects. This research is critical for developing sustainable solutions to mitigate and manage soil salinization.

According to the reports, Dharmapuri district in Tamil Nadu is significantly impacted by soil salinization, affecting approximately 2% of its land [4]. The soil salinity area has increased substantially from 12 to 58% in the drought-affected areas of the study re-

gion. Dharmapuri district is a dry and semi-arid production system facing high temperatures and inadequate rainfall, accelerating the soil salinization rate [5]. Since the region plays a significant role in agriculture and the economy, it becomes crucial to map soil salinity accurately and identify an appropriate model.

Though a considerable no of empirical and semi-empirical soil salinity indices have been developed using multispectral and SAR products, the performance of such models is subjected to various environmental parameters [6]. Hence, it is essential to understand their applicability across diverse environmental conditions. This study's primary goal is to evaluate the performance of different soil salinity indices and dielectric simulations using Sentinel-1, Sentinel-2, and Landsat 8 OLI (Operational Land Imager) data products to recommend the most promising one for the study region. The present study is centered on substantiating the results of different salinity indices with in-situ measurements through statistical analysis.

2. Materials and Methods

2.1. Study Area and Field Investigation

Dharmapuri, situated in the northwestern climatic zone of Tamil Nadu, India was selected as a study region for this research. The region is found with the variety of soil types, including typic haplustalfs, typic ustorthents, typic ustropepts, typic ustropepts with exposed rock formations, typic rhodustalfs, lithic ustropepts, lithic ustorthents, and rhodic paleustalfs in which the predominant soil types consist of loam and clay. The pH levels in this area is found to be alkaline [7].

A field investigation was conducted on Palacode Taluk of Dharmapuri district, and around 60 soil and water samples were collected. The soil samples collected under dry conditions were tested for their Soil Electrical conductivity (EC) levels in the field using a digital soil water analysis kit. For the soil samples observed under irrigated conditions, the samples were kept in zip lock covers (to preserve the field moisture content) for laboratory measurements. The samples were then calibrated for field moisture conditions to measure the dielectric measurements using a laboratory Microwave Analyzer (N9951A). This analysis aimed to investigate the imaginary part of the dielectric constant (that represents soil salinity) of the soil samples at C-band frequency (5.36 GHz) under varying moisture levels.

2.2. Multispectral Data and Soil Salinity Indices

Multispectral remote sensing data products, namely Landsat and Sentinel-2, have been employed in this present study. Landsat 8 OLI consists of 11 bands, including PAN (band 8 with a spatial resolution of 15m), Visible & SWIR (bands 1-7 with a spatial resolution of 9 - 30m), and TIR (band 10 to 11 with a spatial resolution of 100m). The Sentinel-2 (carrying the Multispectral Imager) delivers 13 spectral bands ranging from 10 to 60-meter pixel size. The most widely used multispectral salinity indices, including Salinity Index-1, Salinity Index-2, Salinity Index-3, Salinity Index-4, Salinity Index-5, Salinity Index-6, Salinity Index-7, and Modified Salinity Index (MSI), were chosen for this study based on their varying prediction performance demonstrated in the previous studies [8,9,10]. These indices were utilized to estimate the soil salinity levels from Landsat and Sentinel-2 data products, as indicated in Table 1.

Table 1. Salinity Indices and their equations.

Satellite data	Salinity Index	Equation	Reference
Landsat 8 OLI	Salinity Index-1	$(B^*R)^{0.5}$	11
	Salinity Index-2	$(G^*R)^{0.5}$	12
	Salinity Index- 3	$(G^2 + R^2)^{0.5}$	11
	Salinity Index- 4	$(G^2 + R^2 + NIR^2)^{0.5}$	11
	Salinity Index- 5	$(B^*R)/G$	13

	Salinity Index- 6	(NIR*R)/G	13
	Salinity Index- 7	(G+R)/2	12
	Modified Salinity Index (MSI)	$\frac{\sqrt{(NDVI_i^2 + TIR_i^2)}}{(1 + NDVI_i)}$	5
Sentinel- 2	Salinity Index- 1	(B*R) ^{0.5}	11
	Salinity Index- 2	(G*R) ^{0.5}	12
	Salinity Index- 3	(G ² + R ²) ^{0.5}	11
	Salinity Index- 4	(G ² + R ² + NIR ²) ^{0.5}	11
	Salinity Index- 5	(B*R)/G	13
	Salinity Index- 6	(NIR*R)/G	13
	Salinity Index- 7	(G+R)/2	12

2.3. Sentinel 1 Data and Dielectric Models

The multilooked Ground range detected (GRD) Sentinel 1 product acquired in VV and VH polarization modes with an incidence angle ranging from 30.09° to 36.82° was instrumental in this study. The semi-empirical SAR simulations, namely the Density space dielectric model for Soil Salinity (DSDM-SS) [14] (Equation 1) and simplified Hallikainen models [15, 16] (Equation 2), were employed to retrieve the imaginary part of the dielectric constant and compared to find the best-fit model.

$$\epsilon'' = \frac{\sqrt{(\sigma_{vv-max}^o - \sigma_{vv-i}^o) + STI_i^2}}{\cos \left[\tan^{-1} \left(\frac{\epsilon (NS)_{field-max}(\mu)}{2D - SDM(NS)_{max}(\mu)} \right) \right]} - \frac{\sqrt{(\sigma_{vv-max}^o - \sigma_{vv-i}^o) + STI_i^2}}{\cos \left[\tan^{-1} \left(\frac{\epsilon (S)_{field-max}(\mu)}{2D - SDM(S)_{max}(\mu)} \right) \right]} \tag{1}$$

Where σ_{vv-max}^o , σ_{vv-i}^o , STI, $\epsilon (NS)_{field-max}(\mu)$, $2D - SDM(NS)_{max}(\mu)$, and $2D - SDM(S)_{max}(\mu)$ stand for maximum value of VV polarized product, *i*th value of VV polarization, Soil Textural Index, field-measured dielectric constant of non-saline soils, and field-measured dielectric constant of the saline soils.

$$\epsilon'' = a_0 + a_1S + a_2C + b_0 m_v + b_1Sm_v + b_2Cm_v + C_0m_v^2 + C_1Sm_v^2 + C_2Cm_v^2 \tag{2}$$

Where, S and C represents sand and clay percent in the soil, m_v stands for volumetric moisture content and $a_0, a_1, a_2, b_0, b_1, b_2, C_0, C_1, C_2$ are the calibration coefficients. The field-observed electrical conductivity values were considered in solving the linear equation to obtain the values of these calibration coefficients.

2.4. Statistical Analysis with In-Situ Measurements

The correlation coefficient analysis was carried out between the resultant products of salinity retrieved from the different multispectral and SAR models and the field observations from the 60 sampling locations. The statistical parameters, namely Correlation coefficient (R²) (Equation 3), Root mean square error (RMSE) (Equation 4) and Mean absolute error (MAE) (Equation 5), were used to substantiate and compare the significance of the results.

$$R^2 = \frac{\sum(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum(x_i - \bar{x})^2 \sum(y_i - \bar{y})^2}} \tag{3}$$

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (x_i - y_i)^2} \tag{4}$$

$$MAE = \frac{1}{N} \sum_{i=1}^N (x_i - y_i) \tag{5}$$

Where, x_i represents the observed value of salinity from the field measurements, \bar{x} represents the mean of the values of the x variable, y_i represents the predicted value of salinity obtained from remote sensing simulations, \bar{y} represents the mean of the values of the y variable, and N represents the total number of samples.

3. Results and Discussions

The results obtained from various salinity indices derived from Landsat 8 OLI and Sentinel 2 imageries were validated using the field-scale soil EC measurements obtained from the soil water analysis kit. The R^2 values for different multispectral salinity models for the same study region ranged from 0.43 to 0.89. It was evident from the results of the salinity indices that the MSI has shown the best prediction performance to map the salinity in the soils under dry conditions ($R^2=0.88$, $RMSE= 0.022$, $MAE=-0.011$). The higher accuracy of MSI over other band combinations shows that the inclusion of the thermal band had significantly increased the performance of the index. However, the indices derived from Sentinel 2 were more accurate than those with the same band combination from Landsat 8. Salinity Index- 4 derived from Sentinel 2 have shown an accuracy with a R^2 value 0.79, followed by Salinity Index-5 with a R^2 value of 0.77. Salinity Index-2, 3 and 7 proved insignificant because of their poor correlation with field values (Landsat: $R^2 = 0.45$, $RMSE = 0.046$, and $MAE = 0.015$; $R^2 = 0.56$, $RMSE = 0.136$, $MAE = -0.131$; $R^2 = 0.43$, $RMSE = 0.300$, $MAE = 0.186$ respectively ; Sentinel-2: $R^2 = 0.62$, $RMSE = 0.046$, $MAE = -0.003$; $R^2 = 0.59$, $RMSE = 0.112$, $MAE = -0.099$; $R^2 = 0.45$, $RMSE = 0.210$, $MAE = -0.199$ respectively) results of the poorly correlated indices).

Aylin et al., (2019) have studied and compared the applicability of various salinity indices in Urmia Lake basin, situated in the North-Western part of Iran. The results from the study shown a range of R^2 from 0.50 to 0.78 for the models derived from sentinel-2 imageries which is similar to the present study. In another study, Elhag (2015) applied landsat imagery based salinity indices in Wadi Al Dawasir Town, Riyadh and their results have an R^2 value ranging from 0.40 to 0.95 in which salinity Index-6 (NIR*R)/G) have the higher accuracy of $R^2 = 0.98$. Similarly in the present study, salinity Index-6 derived from landsat 8 was showing an accuracy of $R^2 = 0.76$ followed by modified salinity index. Shoba and Ramakrishnan (2016) reported performance of the MSI ($R^2 = 0.80$) in predicting soil salinity in their study which has shown slightly higher performance in the present study with an R^2 value of 0.88 with the ground EC measurements. Since the study regions belong to dry climatic conditions, most of the time, the soils might be in the dry state, and MSI proves to be the best in predicting dry state salinity. Figure 1(a) shows the statistical significance of the salinity indices derived from Landsat 8 and Sentinel 2 with field soil EC values.

Table 2. Statistical performance of different salinity indices and models.

Satellite data	Salinity Indices/ Models	R^2	RMSE	MAE
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Landsat 8 OLI	Salinity Index-1	0.65	0.028	0.007
	Salinity Index-2	0.45	0.046	0.015
	Salinity Index- 3	0.56	0.136	-0.131
	Salinity Index- 4	0.75	0.020	0.001
	Salinity Index- 5	0.76	0.009	0.001
	Salinity Index- 6	0.76	0.017	-0.001
	Salinity Index- 7	0.43	0.300	0.186
	Modified Salinity Index (MSI)	0.88	0.022	-0.011
Sentinel 2	Salinity Index-1	0.64	0.011	-0.056
	Salinity Index-2	0.62	0.046	-0.003
	Salinity Index- 3	0.59	0.112	-0.099
	Salinity Index- 4	0.79	0.014	0.002
	Salinity Index- 5	0.77	0.024	0.004
	Salinity Index- 6	0.70	0.006	-0.007
	Salinity Index- 7	0.45	0.210	-0.199
Sentinel 1	DSDM	0.67	0.094	-0.251
	Hallikainen Model	0.89	0.018	0.105

Similarly, by analyzing the dielectric models, the imaginary part of the dielectric constant was found to be highly sensitive to soil salinity, and hence, it is directly accounted for wet state salinity. The results from dielectric models were validated with the field-scale dielectric loss estimated from a microwave network analyzer. The Simplified Hallikainen model outperformed the DSDM-SS model with an increased R^2 value of 0.89. This was due to the limitation of the applicability of the DSDM-SS model towards free water conditions prevailing in the sandy soil [14]. Since some part of the study region is irrigated agriculture, the Hallikainen model was found to be the best fit for estimating soil salinity. Periasamy and Ravi (2020) proposed DSDM-SS model and it was showing high accuracy of $R^2 = 0.88$ in predicting salinity, but which was found decreasing to $R^2 = 0.76$ according to the increase in clay content of the soil from 7% to 48%. According to the study conducted by Periasamy and Shanmugam (2017), Imaginary part of dielectric constant derived from Hallikainen’s model finds to be increasing with the increase in clay content. R^2 value between imaginary part and in-situ dielectric loss increased from 0.68 to 0.72 when the clay percent increased from 45% to 60% which shows the suitability of Hallikainen’s model in predicting salinity in clayey soil. Figure 1(b) shows the statistical significance of both the models validated with in-situ dielectric loss estimates. The values of the simulations and field measurements were normalized from 0 to 1 in figure 1.

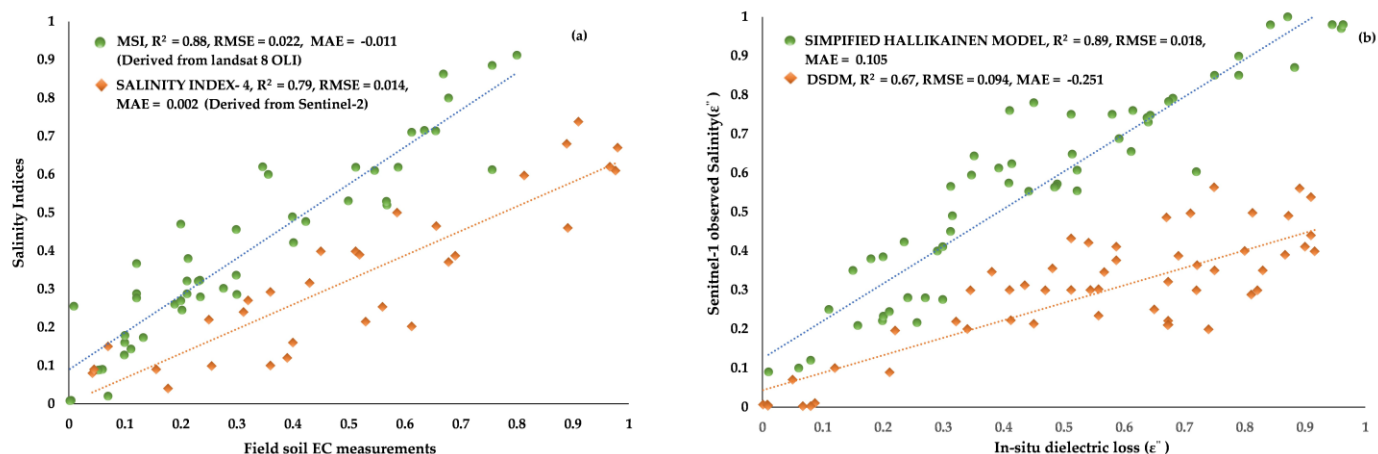


Figure 1. (a, b) The statistical significance of the model validated with in-situ observations.

4. Conclusion

It is crucial to monitor and analyze changes in soil salinity over time to effectively devise strategies in natural resource management. The study area is severely affected by soil salinity under both dry and wet conditions, so it's important to find the best-fit model for salinity assessment. According to the analysis, the Simplified Hallikainen model is the best representation for wet state salinity, while the Modified Salinity Index is accurate for estimating dry state salinity. However, it's worth noting that the models' performance may vary from region to region, depending on environmental and geographic patterns.

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