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Soil Salinity Mapping using Sentinel 2 for Agricultural Land Areas in Lagoon and Coastal Regions of Hue City, Vietnam

Pham Huu Ty[1], Tran Thi Minh Chau[1], Ha Nam Thang[1], Nguyen Hoang Khanh Linh[2], Pham Gia Tung[2]

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ABSTRACT

Background: Soil salinity maps are crucial for agricultural development and soil quality improvement. However, the optimal techniques for soil salinity mapping using remote sensing remain debatable. Coastal and lagoon regions, such as those in Hue City, Vietnam, are particularly vulnerable to soil salinization, which can significantly impact land use and crop productivity.

Methods: This research was conducted in two communes within the lagoon and coastal region of Hue City, Vietnam. Sentinel-2 satellite imagery and ground measurements of soil electrical conductivity (EC) were collected and analyzed. Simple and multiple linear regression models were developed using spectral indices as input features to estimate soil salinity.

Result: The multiple linear regression model incorporating SI3 and NDVI achieved a strong performance with an R^2 of 0.84 and an RMSE of 0.52 dS/m, while the SI3 index is the most suitable for a simple regression model. Significant differences in soil salinity were observed among land use types, with coastal forest lands exhibiting the highest EC values and paddy rice fields the lowest. These findings demonstrate the accuracy and usefulness of remote sensing techniques for monitoring soil salinity, providing valuable data for preventing soil degradation and supporting sustainable agricultural practices.

Key words: Agricultural land, Hue city, Lagoon region, Sentinel 2, Soil salinity mapping.

INTRODUCTION

The agricultural land has a vital role for the development because it is relevant to 11 of the 17 sustainable development goals (Viana *et al.,* 2022). Especially in developing countries, agriculture not only ensures food security but also provides the foundation for economic activities *via* the export of agricultural products Pawlak and Kołodziejczak, (2020). However, agricultural land is currently facing serious problems related to land degradation due to the impacts of climate change and human activities Abdel Rahman, (2023). One of the performances of land degradation is salinization. Soil salinization is a sequence from both natural factors and human activities such as the mineralogy of the parent material, topography, water table quality and irrigation during the agricultural production (Stavi *et al.,* 2021). In the overall, saline soil is a big problem due to many negative impacts on human life in all aspects related to nature, society and economy (Hadj-miloud *et al.,* 2024). In this context, the determination of soil salinity level plays an important role. Remote sensing technologies have emerged as powerful tools for large-scale salinity assessment, offering spatially consistent and cost-effective alternatives to traditional field methods (Kumar *et al.,* 2021; Morgan *et al.,* 2018). Since soil salinity is closely correlated with plant health, most studies use satellite vegetation indices to estimate soil salinity (Ramos *et al.,* 2020). The vegetation indices reflect the information of crop *via* the different of wavebands. In the soil salinity estimation, the Normalized Differential Vegetation Index (NDVI), Soil Adjusted Vegetation Index (SAVI), Canopy Response Salinity Index (CRSI) are most popular to use for the regression model (Ramos *et al.,* 2020). The accuracy of vegetation indices for assessing soil salinity can be inconsistent because they primarily reflect plant health, which may be influenced by other factors than salinity (Allbed and Kumar, 2013). In Vietnam, coastal agriculture is the sector most affected by salinity, due to the effects of high tides, climate change and farming practices (Thach *et al.,* 2023). In salinity-affected areas, rice and corn yields are significantly lower compared to other regions (Nguyen and Tran, 2020). However, the establishment of soil salinity maps in Vietnam has been limited, with only a few studies conducted in the Mekong Delta. Consequently, this study aims (i) to evaluate the potential of salinity and vegetation indices derived from Sentinel data for soil salinity mapping in the coastal and lagoon environments of Central Vietnam

[1]University of Agriculture and Forestry, Hue University, Hue city, Vietnam.
[2]International School, Hue University, Hue city, Vietnam.

Corresponding Author: Pham Gia Tung, International School, Hue University, Hue city, Vietnam.
Email: phamgiatung@hueuni.edu.vn

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and (ii) to assess the saline situation within the study area and propose informed recommendations for adaptive agricultural land use practices. The research area encompasses Phu Da town and Vinh Xuan commune, which belongs to Phu Vang district, Hue city, Vietnam, with location at 16024′N to 16029′N and 107042′E to 107048′E. This region is a part of the largest lagoon system in Southeast Asia, called Tam Giang - Cau Hai.

MATERIALS AND METHODS

Soil samplings and electrical conductivity measurements

There are 50 soil samples that were collected randomly in March of 2024 for five land use types (LUTs), as in Fig 1, at the depth of 0-30 cm. The soil samples were air-dried and ground by 2 mm sieve and then the solution of distillation water to soil mass ratio of 5:1 was used to calculate the $EC_{1:5}$ at the Soil Science Laboratory of Hue University of Agriculture and Forestry. The Hana's EC measurement tool (HI98311) was used to measure the EC value. The suggestion of the United States Department of Agriculture was used for salinity classification based on the EC value, as shown in Table 1. The formula of Sonmez *et al.* (2008) was applied to convert to EC value.

$$EC = 8.22 * EC_{1:5} - 0.33 \quad \text{... (1)}$$

Spectral indices calculation

Sentinel 2A scene of March, 5th, 2024 was used in order to captured simultaneously with soil sampling time. Accordingly, this study used four bands of Sentinel 2 to calculate eight indices which were widely used in previous research (Salem and Jia, 2024), as shown in Table 2.

Regression analysis and accuracy assessment

The simple linear regression (SLR) and multiple linear regression (MLR) models are applied for the predicted model. Three indicators to evaluate the accuracy of the predicted model: Root mean square error (RMSE), Coefficient of Determination (R^2) and Akaike Information Criterion (AIC). In addition, after identifying the most suitable MLR model, we employed the Variance Inflation Factor (VIF) to assess multicollinearity among the variables within the selected model. Only those equations with VIF values less than 3 (Sarabia and Ortiz, 2009) were deemed acceptable for further evaluation of model fit. We evaluated the statistical significance of differences in mean EC values across different LUTs using Dunn's post-hoc test. This analysis was conducted with a 95% confidence level. All indicators were calculated using suitable packages available in the RStudio software environment.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(y_o - y_p)^2}{n}} \quad \text{... (2)}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_o - y_p)^2}{\sum_{i=1}^{n}(y_o - \overleftrightarrow{y}_o)^2} \quad \text{... (3)}$$

$$AIC = 2K - 2\ln(L) \quad \text{... (4)}$$

Where,

y_o = Measured EC value.

y_p= Predicted EC value.

$\overleftrightarrow{y}_o$ = Mean of all the measured EC value.

n = Number of samples.

K = Number of independent variables used (include dependent variable).

L = Log-likelihood estimate.

RESULTS AND DISCUSSION

Electrical conductivity and spectral indices of ground points

The maximum EC recorded was 7.8 dS/m, while the minimum value was 2.8 dS/m. The average EC across all sample points was found to be 4.25 dS/m, with a standard deviation of 1.30 dS/m. Eight maps describing vegetation

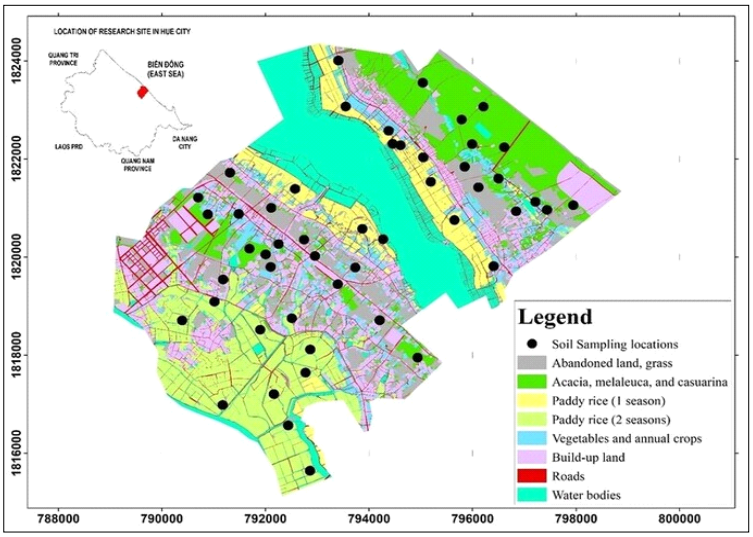


Fig 1: The location of research site in Hue city, land use types and soil sample locations.

and salinity indices are presented in Fig 2. The data from Fig 2 shows that the SI_T, SI1 and SI3 indices are significantly lower in vegetated areas compared to other land types, while the SI2 index is lowest in water-covered areas. The vegetation indices (NDVI, SAVI, EVI and CRSI) indicate the extent of vegetation cover across the study area, highlighting that the southwestern region-primarily used for double-cropped rice cultivation-has the highest vegetation density.

The data corresponding to these eight indices collected from 50 sampling points are detailed in Table 3. The standard de*via*tion (SD) values, which have been calculate based on packages in R studio software, of the indices for rice land use are consistent. This consistency can be attributed to the synchronized implementation of the crop calendar, which has been applied for rice cultivation. In contrast, other LUTs exhibit higher SD values due to the diversity of crops and varying planting times.

The correlation between the EC values and the salinity and vegetation indices is illustrated in Fig 3. The Pearson correlation indicates that the EC index is positively correlated with the salinity indices (SI_T, SI1, SI2, SI3) and negatively correlated with the vegetation indices (NDVI, SAVI, EVI, CRSI). Most correlation values are greater than 0.7, with the exception of the SI2 index, which has a correlation value of 0.35.

Table 1: Classification of soil salinity for agricultural land uses.

Classification	EC value (dS/m)
None-saline soils	0-2
Slightly saline soils	2-4
Saline soils	4-8
Strongly saline soils	8-16
Extremely saline soils	>16

The nature of soil salinity is divided into two types: primary and secondary, in which primary is the salinity process generated by the nature of the elements that make up the soil, while secondary is mainly formed from land use, especially for agricultural land Gojiya *et al.* (2023). Our study area is located near the sea and lagoons and is characterized by active agricultural practices. As a result, the mechanisms of soil salinization are quite complex, involving both primary and secondary processes. In addition, ecological conditions also affect the EC concentration in soil. Some recent studies have shown that vegetation indices can be used to determine EC content in agricultural land (Haq *et al.,* 2023), while others have suggested that SI indices can be used to determine EC content in bare, grass land and uncovered areas (Luo *et al.,* 2025). Recent study used NDVI or EVI as referent classification for soil salinity levels (Djuraev *et al*., 2021). On the contrary, others (Zhang *et al.,* 2011) stated that these indices completely unable to detect soil salinity. In our viewpoint, the lack of significant vegetation cover in their arid study area likely explains this finding. Our results also found that the SI3 index has a strongest correlation to EC value, so it is a good indicator to estimate soil EC. This finding was confirmed by the previous research (Douaoui *et al.,* 2006).

The regression models to estimate soil saline for coastal and lagoon areas

Fig 4 presents scatter plots comparing predicted and measured EC values using various salinity and vegetation indices. Each plot includes a regression equation, coefficient of determination (R^2), Akaike Information Criterion (AIC) and root mean square error (RMSE), which collectively assess model accuracy and fit. SI3 yielded the highest prediction accuracy, with an R^2 of 0.82, AIC of 88.22 and RMSE of 0.55, indicating a strong correlation between

Table 2: Salinity indices and vegetation indices.

Full name	Abbre*via*tion	Formula	Reference
Salinity Index-tripathi	SI_T	$\frac{Red}{NIR} \times 100$	Nitin *et al.* (1997)
Salinity Index 1	SI1	$\sqrt{Green \times Red}$	Douaoui *et al.* (2006)
Salinity Index 2	SI2	$\sqrt{Green^2 + Red^2 + NIR^2}$	Tola *et al.* (2024)
Salinity Index 3	SI3	$\sqrt{Green^2 + Red^2}$	Tola *et al.* (2024)
Normalized difference vegetation index	NDVI	$\frac{(NIR - Red)}{(NIR + Red)}$	(Gerardo and de Lima, 2022)
Soil adjusted vegetation index	SAVI	$\frac{(NIR - Red)}{(NIR + Red + 0.5)} *(1 + 0.5)$	(Huete, 1988)
Enhanced vegetation index	EVI	$2.5 * \frac{(NIR - Red)}{(NIR + 6 * Red - 7.5 * Blue + 1)}$	Zhen *et al.* (2023)
Canopy response salinity index	CRSI	$\sqrt{\frac{(NIR * Red) - (Green * Blue)}{(NIR * Red) + (Green * Blue)}}$	Tola *et al.* (2024)

Table 3: Spectral indices values and land use types.

Index	Criteria	Abandoned land, grassland	Acacia, Melaleuca, Casuarina	Vegetables and annual crops	Paddy rice (1 season)	Paddy rice (2 seasons)
SI_T	Min	34.84	47.07	28.17	24.19	20.86
	Max	82.14	80.80	61.16	72.03	29.22
	Mean	59.94	60.83	46.09	37.56	24.16
	SD	17.98	11.42	8.20	12.68	2.70
SI1	Min	0.130	0.130	0.130	0.130	0.120
	Max	0.340	0.360	0.190	0.180	0.130
	Mean	0.220	0.191	0.154	0.140	0.127
	SD	0.076	0.069	0.020	0.016	0.005
SI2	Min	0.39	0.33	0.34	0.35	0.46
	Max	0.65	0.69	0.49	0.54	0.59
	Mean	0.49	0.42	0.40	0.43	0.54
	SD	0.09	0.11	0.04	0.05	0.05
SI3	Min	0.190	0.190	0.180	0.180	0.180
	Max	0.480	0.510	0.260	0.260	0.190
	Mean	0.312	0.273	0.218	0.203	0.183
	SD	0.106	0.097	0.029	0.023	0.005
NDVI	Min	0.09	0.10	0.24	0.16	0.54
	Max	0.48	0.35	0.56	0.61	0.65
	Mean	0.26	0.24	0.37	0.46	0.61
	SD	0.15	0.09	0.08	0.12	0.03
SAVI	Min	0.09	0.10	0.18	0.11	0.43
	Max	0.36	0.25	0.45	0.51	0.56
	Mean	0.20	0.18	0.27	0.35	0.51
	SD	0.10	0.05	0.07	0.10	0.05
EVI	Min	0.11	0.15	0.21	0.17	0.60
	Max	0.48	0.31	0.60	0.71	0.82
	Mean	0.28	0.25	0.38	0.50	0.74
	SD	0.13	0.05	0.10	0.14	0.07
CRSI	Min	0.43	0.51	0.58	0.43	0.70
	Max	0.67	0.63	0.70	0.73	0.76
	Mean	0.55	0.58	0.63	0.64	0.73
	SD	0.08	0.04	0.03	0.08	0.02

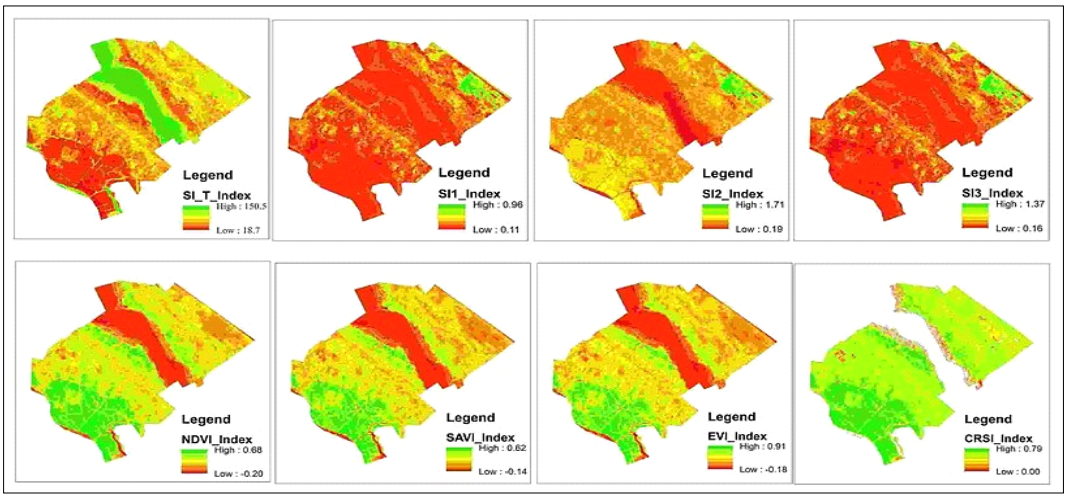


Fig 2: Eight indices extracted from Sentinel 2 image.

predicted and observed EC value while SI2 exhibited the poorest model fit (R^2 = 0.12, RMSE = 1.22), indicating it is not a reliable indicator for predicting EC in this study area.

Table 4 presents the MLR models developed using stepwise selection based on the AIC. The MLR models exhibit significantly higher accuracy compared to SLR models. Although the model combining SI3, EVI and NDVI (Model 6) shows an approximately 2% higher RMSE and a 1.1% lower R^2 compared to the others, it achieves the lowest AIC score of 83.43 and uses the fewest variables. The technique to mitigate multicollinearity among the variables in the model for the model of SI3, NDVI and EVI variables.

Fig 5 shows six scatter plots, each representing a different model (Model 1 to Model 6). Each plot compares predicted EC (X-axis) values to measured EC values (Y-axis). As illustrated in the figure, the differences among the models are not markedly significant. A notable feature across the models is that data points corresponding to the highest values deviate substantially from the 1:1 reference line. This suggests that for extreme EC values, factors beyond those captured by remote sensing data may be influencing the results, indicating the need to incorporate additional variables or contextual information to improve model accuracy.

Fig 6 shows that only two of four models, those combining SI3 with NDVI and SI3 with EVI, exhibited a multicollinearity index of less than 3, which meets the criteria for acceptable use. The model combining SI3 with NDVI, (EC= 2.22+11.47*SI3-1.78*NDVI) has the lowest AIC

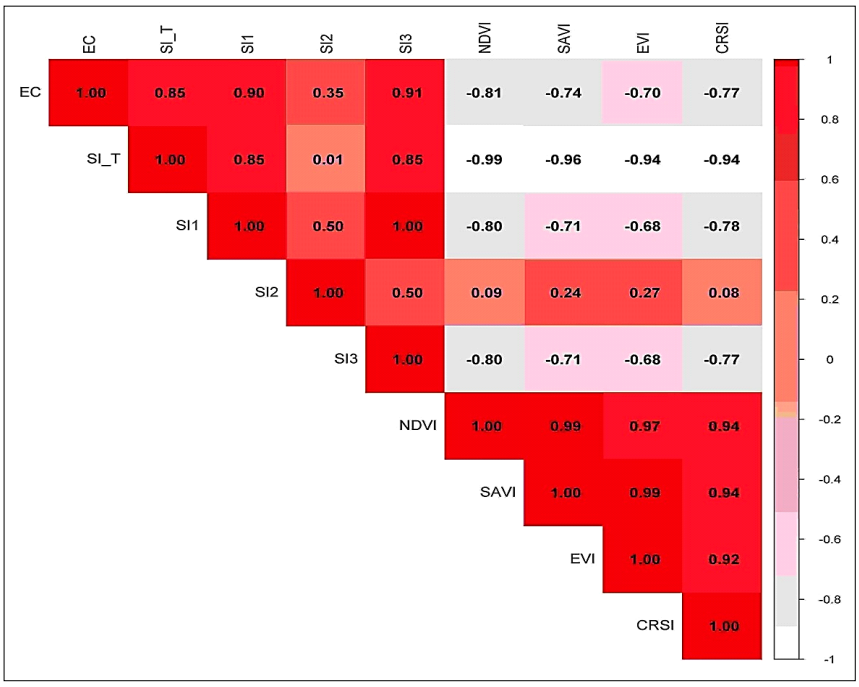


Fig 3: Pearson correlation of spectral indices and EC values.

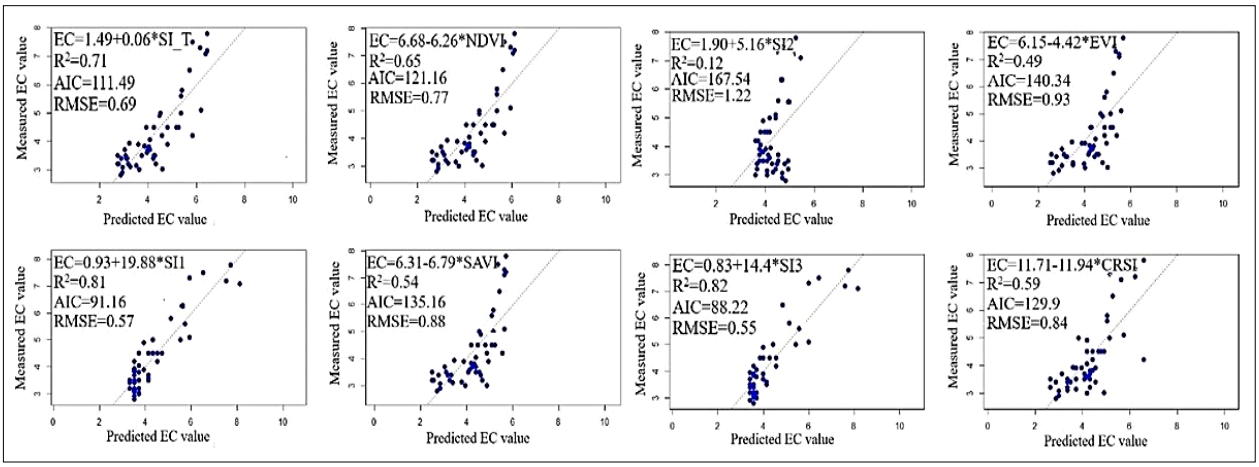


Fig 4: Relationship between the predicted and measured EC values of SLR models.

and RMSE coefficients (84.6 and 0.52), as well as the highest R^2 value with a value of 0.84. We recommend this model for estimating salinity in the coastal sandy areas and lagoons of Hue city. Linear regression models are widely utilized in soil salinity mapping Al-Ali *et al.* (2021), among them MLR models tend to be more accurate than SLR models Al-Khuzaie *et al.* (2022). This is because MLR models take into account a greater number of factors, reducing the likelihood of overlooking important variables that affect soil salinity compared to simpler models. However, in certain situations, simple models can still yield satisfactory results, serving as a foundation for further analysis or the application of more complex models Hihi *et al.* (2019).

Agricultural land management adapt to soil saline situation

Fig 7 illustrate the spatial distribution of soil salinity across agricultural land areas, as determined by the selected MLR model (EC= 2.22+11.47*SI3-1.78*NDVI). The findings

Table 4: The parameters of MLR models.

RMSE	AIC	R^2	VIF							
			SI_T	SI1	SI2	SI3	NDVI	SAVI	EVI	CRSI
Model 1: EC=5.10-0.04*SI_T-20.39*SI1-4.52*SI2+30.96*SI3-11.93*NDVI-2.45*SAVI+7.78*EVI+1.72*CRSI										
0.49	89.88	0.86	544	356	183	267	884	834	97	16
Model 2: EC=4.80-0.04*SI_T-18*SI1-6.01*SI2+31.32*SI3-12.81*NDVI+7.69*EVI+1.82*CRSI										
0.49	87.91	0.86	515	283	61	261	731		95	16
Model 3: EC=1.53+14.76*SI1-7.33*SI2+29.82*SI3-8.42*NDVI+7.45*EVI+2.43*CRSI										
0.49	86.08	0.86		219	44	243	61		92	12
Model 4: EC=2.91-18.34*SI1-5.15*SI2+29.04*SI3-7.64*NDVI+6.57*EVI										
0.49	84.78	0.86		206	33	29	55		82	
Model 5: EC=2.87-5.61*SI2+16.72*SI3-7.41*NDVI+6.66*EVI										
0.5	83.93	0.85			33	60	55		82	
Model 6: EC=3.37+8.87*SI3-7.38*NDVI+3.84*EVI										
0.5	83.43	0.85				5	55		37	

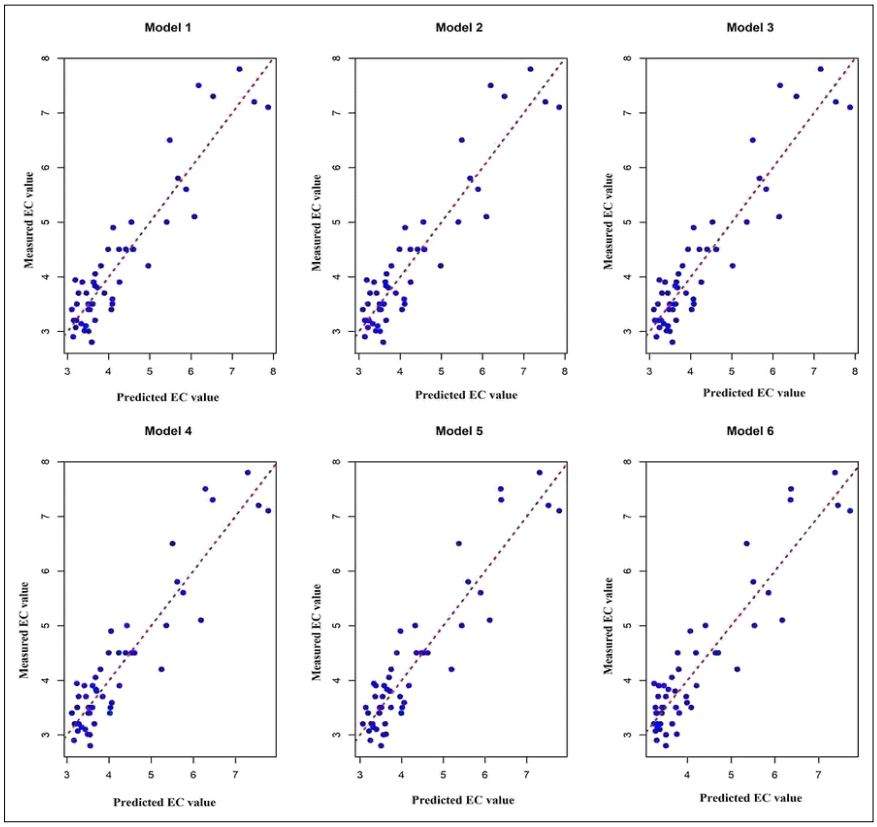


Fig 5: Relationship between the predicted and measured EC values of MLR models.

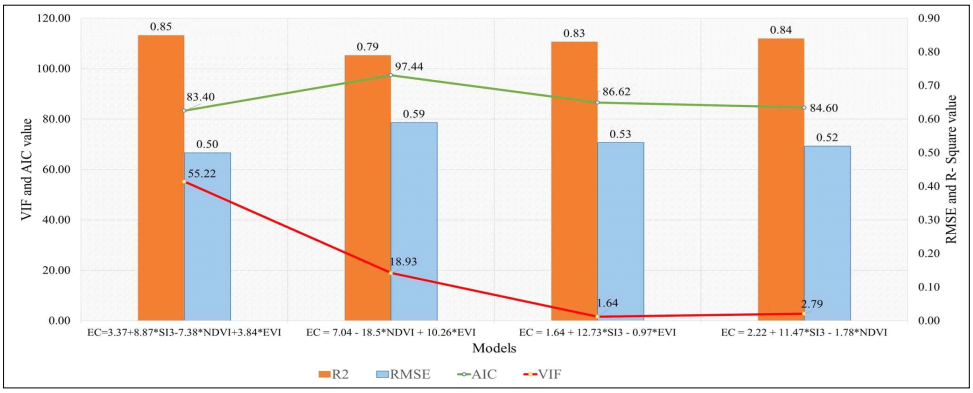


Fig 6: The statistics of the accuracy indicators for the models of using SI3, NDVI and EVI.

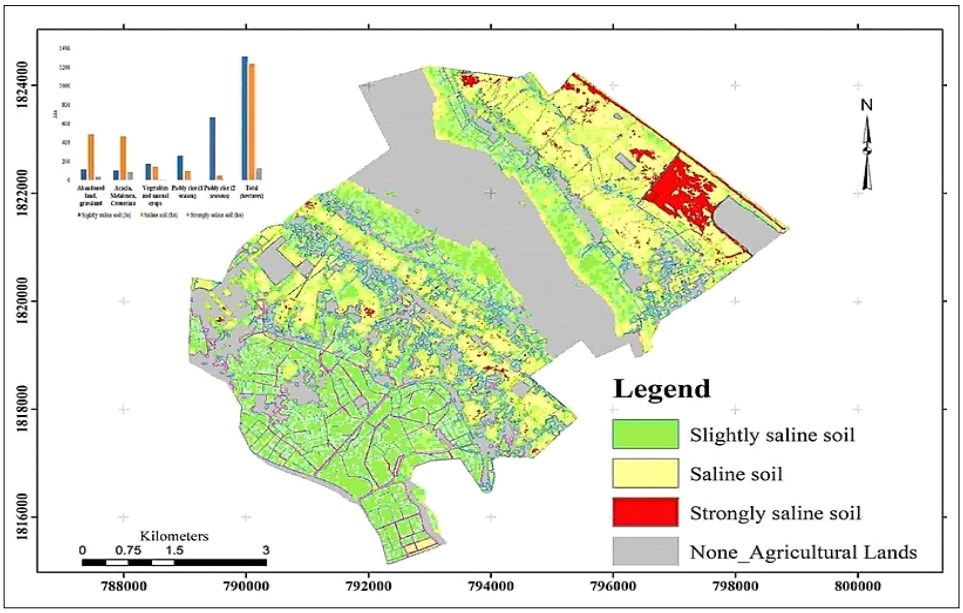


Fig 7: Soil salinity map of agricultural land areas.

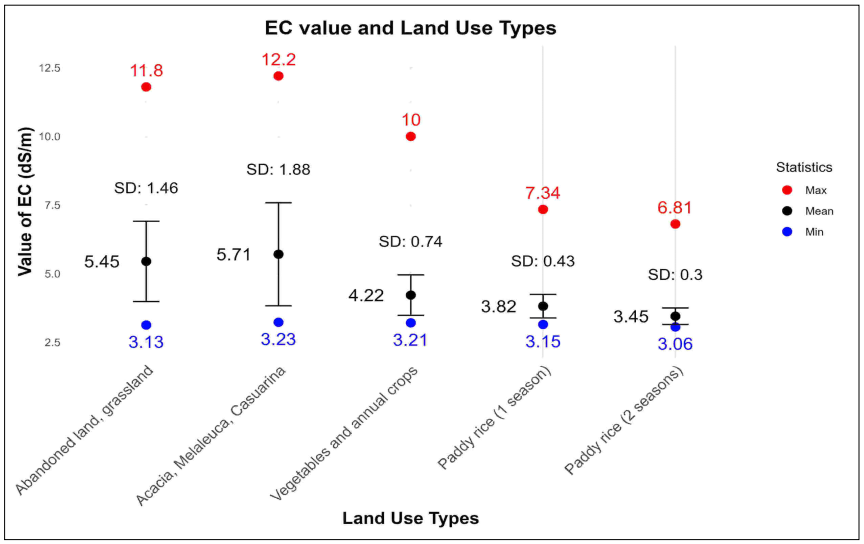


Fig 8: The statistical predicted EC values based on land use types.

indicate that all agricultural land within the study site exhibits salinity.

A Dunn depth analysis was conducted at a 95% confidence level on all points (where each pixel represents a point) across various LUTs as shown in Fig 8. The results indicated a statistically significant difference in the mean EC values among the LUTs.

Irrigation and fertilization significantly impact the soil EC content (Thiam *et al.,* 2021). Our results show that two-seasons paddy rice areas have the lowest EC due to frequent flooding in November, which washes salts away, consistent with recent study Shirokova *et al.* (2024). Single-season rice fields, adjacent to lagoons with higher salinity water, have higher EC than two-seasons paddy rice areas. Coastal forests dominated by Acacia, Melaleuca and Casuarina show the highest salinity, as these species tolerate saline soils (Khalil *et al.,* 2016). We suggest planting coconut trees in these areas for economic and salinity tolerance benefits (Sun *et al.,* 2024). Abandoned lands accumulate surface salts with high EC; revegetation with native grasses is recommended to improve the soil gradually. Vegetable and annual crop fields show varied EC due to diverse crops and irrigation, but crop selection often ignores salinity tolerance. Current crops such as sweet potato, chili pepper and corn are not suitable for saline soil, so the shifting to more salt-tolerant crops like garlic and pitaya should be considered (Cavalcante *et al.,* 2008). Overall, varying salinity across land uses highlights the need for tailored management to minimize salinity impacts and support sustainable agriculture.

CONCLUSION

In the research site, the linear regression models using eight spectral indices revealed that a combination of SI3 and NDVI (EC= 2.22+11.47*SI3-1.78*NDVI) provided the most accurate salinity estimates. The entire agricultural area was affected: nearly 50% slightly saline, 5% strongly saline and the remainder moderately saline. Coastal forests showed the highest EC, while two-season paddy rice had the lowest. The study suggests cropping pattern adjustments and highlights the potential of multi-temporal/multi-satellite data, along with stakeholder involvement, to improve salinity mapping.

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Disclaimers

The views and conclusions expressed in this article are solely those of the authors and do not necessarily represent the views of their affiliated institutions. The authors are responsible for the accuracy and completeness of the information provided, but do not accept any liability for any direct or indirect losses resulting from the use of this content.

Conflict of interest

The authors declare that there are no conflicts of interest regarding the publication of this article. No funding or sponsorship influenced the design of the study, data collection, analysis, decision to publish, or preparation of the manuscript.

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