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Geospatial Modelling of Soil Fertility and Sodicity Indices in Aridisols of the Sudano-Sahelian Savannah for Sustainable Soil Management

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Abstract

Effective management of Aridisol soils requires a robust understanding of fertility indices as predictors of Exchangeable Sodium Percentage (ESP). Although Soil Organic Carbon (SOC), Cation Exchange Capacity (CEC), and soil pH have been widely studied, their combined influence on ESP prediction remains unclear. This study statistically and geospatially evaluated the relationships between these indices and ESP. Thirty-six composite soil samples (0 - 30 cm depth) were collected using a hybrid sampling method, with geodetic coordinates recorded. Spatial interpolation was performed using Inverse Distance Weighting (IDW) in ArcGIS 10.8, while regression analyses were conducted in Microsoft Excel. IDW interpolation revealed an inverse spatial trend between SOC and ESP, with SOC >2.5% and 1.5–2.5% corresponding to ESP >25% and 10–25%, respectively. Linear regression showed strong positive associations of ESP with CEC ($\beta = 1.41$, $p = 0.0045$) and pH ($\beta = 6.62$), whereas SOC exhibited a weak, non-significant negative relationship ($R^2 = 0.086$, $\beta = -2.70$, $p = 0.52$). The initial multiple regression model displayed moderate predictive strength (adjusted $R^2 = 0.553$). After excluding SOC and noting the reduced significance of pH ($p = 4.36$), CEC emerged as the dominant predictor of ESP variability. The refined model achieved higher accuracy with a root mean square error (RMSE) of 2.91 and an average R^2 of 0.5671 from k-fold cross-validation. These findings underscore CEC as the most influential determinant of ESP in Aridisols, with soil pH exerting moderate influence and SOC contributing indirectly through soil structural effects.

Keywords: Aridisols, hybrid sampling, soil fertility indices, Soil Organic Carbon, Exchangeable sodium percentage

Introduction

Sodicity, expressed as ESP, is a widespread challenge in semi-arid regions where evapotranspiration far exceeds precipitation (Adane *et al.* 2019; Husein *et al.* 2021). ESP generally originates from both natural soil processes and irrigation water, particularly when sodium concentrations surpass those of essential cations such as calcium and magnesium (Dodd *et al.* 2013; Stavi *et al.* 2021). This dominance of Na^+ ions relative to Ca^{2+} and Mg^{2+} disrupts soil chemical balance, creating sodic conditions that compromise soil fertility and health (Hailu and Mehari 2021). Within this context, ESP is widely recognized as a critical indicator of soil degradation, as it represents the proportion of sodium-occupied exchange sites compared to the total cation exchange capacity (Gebrehiwot 2022).

In the Sudano-Sahelian savannah, soils are inherently dry, low in fertility, and subjected to inefficient irrigation practices. These conditions accelerate sodium accumulation, degrade irrigation water quality, and intensify soil chemical imbalances (Pal *et al.* 2016;

Stavi *et al.* 2021; Gebrehiwot 2022; Wang *et al.* 2023; Naorem 2023). Elevated ESP increases soil pH, induces alkaline hydrolysis, reduces the availability of essential nutrients, and alters soil solution chemistry, with serious consequences for soil structure, plant growth, and long-term productivity (Mamedov *et al.* 2006; Yang *et al.* 2016; Stavi *et al.* 2021; Mendieta-Mendoza 2023).

Soil fertility, defined as the ability of soil to supply essential nutrients in forms available for plant uptake (Njoku *et al*. 2011), is central to maintaining productivity and sustainable agriculture. Key fertility indicators such as soil organic carbon (SOC), cation exchange capacity (CEC), and soil pH not only reflect soil nutrient status but also influence sodicity dynamics (Njoku *et al.* 2011; Stavi 2021; Hailu and Mehari 2021; Trigunasih *et al.* 2023). Fertile soils enhance nutrient cycling, maintain balanced cation exchange, and improve structure through organic matter accumulation, all of which contribute to lowering ESP (Saidi 2012; Bao *et al.* 2017; Stavi *et al.* 2021; Wang *et al.* 2023). Conversely, nutrient-depleted soils under sodic stress experience reduced resilience, declining productivity, and constrained land-use efficiency.

Despite its importance, soil fertility assessment in semi-arid environments often relies on conventional approaches that inadequately capture the spatial variability of fertility - sodicity interactions (Njoku *et al.* 2011). In recent years, geoinformatics and geostatistical modelling have emerged as powerful tools for monitoring soil fertility and predicting ESP distribution at multiple scales (Bhunia *et al.* 2016; Khan *et al.* 2019; El-Seedy *et al.* 2024; Jamaoui *et al.* 2025). However, in many regions, local farmers and extension workers still lack reliable and accessible information about soil fertility status and hazardous soil - water interactions, particularly salinity and sodicity (Njoku *et al.* 2011; Adane *et al.* 2019; Husein *et al.* 2021; Baballe *et al.* 2022; El-Seedy *et al.* 2024). This information gap underscores the need for research that integrates field data with spatial modelling to generate accurate, decision-support information for sustainable soil management.

Against this backdrop, the present study investigates the distribution and variability of soil fertility indicators - SOC, CEC, and soil pH - and their relationship with ESP in Aridisol soils of the Sudano-Sahelian savannah. Specifically, the study sought to: (1) assess the spatial variation of fertility indices across the study area; (2) determine the relationship between soil fertility indicators and ESP levels; and (3) quantify the extent to which fertility indices influence ESP both statistically and geospatially. Data were collected through conventional field surveys and analyzed using geoinformatics techniques, allowing for robust modelling of fertility - sodicity interactions.

The findings of this research provide a foundation for sustainable soil management in semi-arid environments. By integrating geostatistical modelling with regression analysis, the study enhances ESP prediction using key fertility indicators, thereby supporting targeted strategies for soil fertility restoration, irrigation water management, and the application of soil amendments. Such approaches contribute to precision agriculture by enabling site-specific nutrient management, reclamation of sodic soils, and efficient allocation of limited resources in fragile environments (de Oliveira *et al.* 2014;

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Baballe *et al.* 2022; Trigunasih *et al.* 2023; El-Seedy *et al.* 2024). Furthermore, the generation of reliable soil information through geoinformatics empowers policymakers, xtension services, and farmers to make informed decisions aimed at reducing soil degradation, mitigating sodium accumulation, and safeguarding long-term land productivity.

Ultimately, this study advances understanding of the complex interactions between soil fertility indices and sodicity under semi-arid conditions. It provides a geostatistical framework for monitoring ESP variability, guiding reclamation and conservation practices, and ensuring sustainable soil health in Aridisol soils of the Sudano-Sahelian savannah.

Materials and Methods

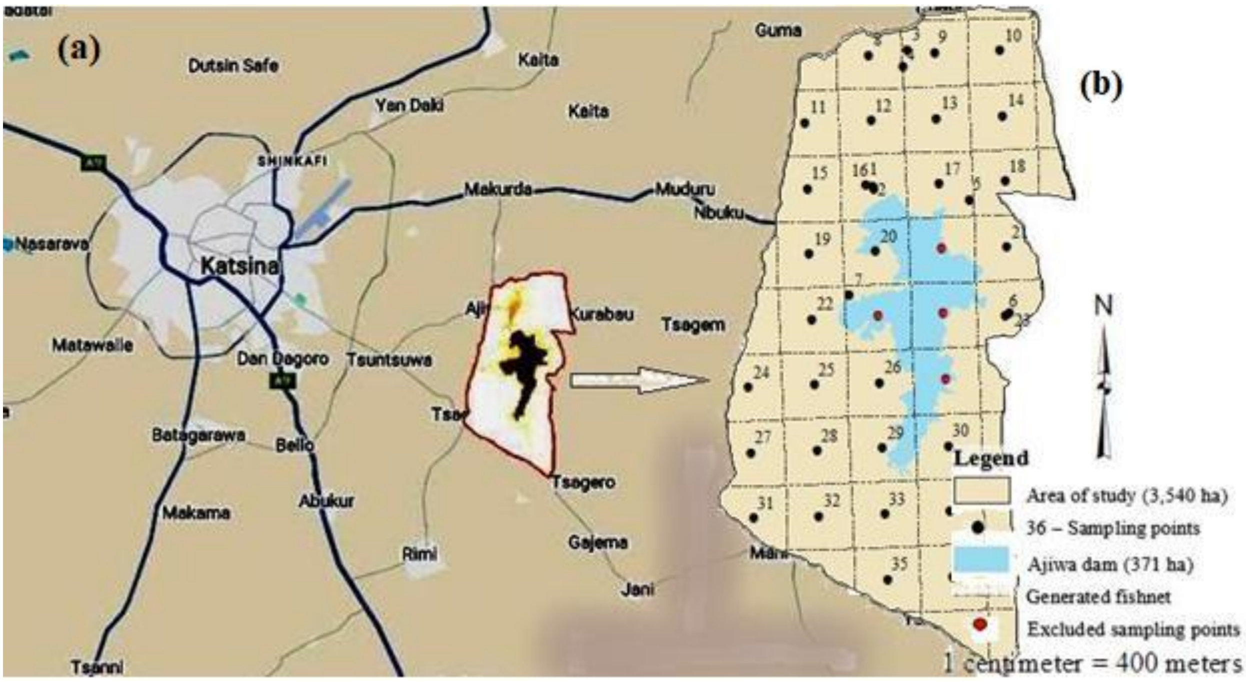

Figure 1: Location of the study area (b) in relation with Katsina town and (a) the extent of the study area - Ajiwa Irrigation Scheme with an area of 35.4 km^2 and presence of dam water body in the mid. Thirty-six sampling points are shown, soil samples collected at 1 - 30 cm depth and intervals of 1,000 m systematic (1 - 7) and purposive (8 - 36): hybridization sampling method (Liu *et al.*, 2024).

Geographical Setting of the Study Area

The study was carried out at the Ajiwa Dam Irrigation Scheme, covering approximately 3,450 ha in Rimi Local Government Area of Katsina State, Nigeria. The scheme lies between longitude 7°43′37.51″E and 7°46′40.81″E, and latitude 12°58′41.56″N and 12°53′9.92″N. The area falls within the semi-arid climatic zone, characterized by a mean minimum temperature of about 15.7°C in January and peak temperatures exceeding 35°C during the hottest months. Rainfall is unimodal, commencing in May and ending in September, with August being the wettest month (≈283.5 mm). According to the USDA Soil Taxonomy, the soils of the area are classified as Aridisols.

Data Collection and Analysis Approach

Soil sampling was carried out in two phases. In the first phase, conducted in February 2025, seven purposively selected samples were collected from sites exhibiting visible whitish encrustations, indicative of surface salinization. In the second phase, undertaken in April 2025, an additional 29 samples were systematically collected at predetermined 1000 m intervals. Sampling grids were generated using the *Create Fishnet Tool* in ArcGIS 10.8 to ensure uniform spatial coverage of the study area (Figure 1).

This process yielded a total of 36 georeferenced sampling points. Field navigation was facilitated using GPS-enabled devices, supported by Locus and Avenza Maps applications, which ensured precise coordinate recording and accurate site tracking. At each location, soil samples were extracted from a depth of 0 - 30 cm using a hybrid sampling technique with a soil auger, consistent with established soil sampling protocols (Liu *et al.* 2024).

Soil Sample Preparation

The fresh soil samples were air-dried at room temperature, sieved through a 2 mm mesh, and homogenized for uniformity (Gee and Bauder 1986). The sieved soils were then finely ground. The representative subsamples were weighed and transferred into clean, labelled containers for subsequent laboratory analyses (Anderson and Ingram 1993).

Determination of Exchangeable Cations (Ca^{2+}, Mg^{2+}, Na^+ and K^+)

About 30 mL of 1 M NH_4OAc solution (pH 7.0) was added to the soil sample, and the mixture was shaken on an orbital shaker at 200 rpm for 30 minutes. It was then centrifuged at 3000 rpm for 10 minutes, after which the supernatant was filtered through Whatman No. 42 ashless filter paper (pore size ~2.5 µm) to obtain a clear extract. Finally, the concentration of extracted cations was measured using Atomic Absorption Spectrophotometer (AAS, PerkinElmer Analyst 400, PerkinElmer Inc., USA). And their corresponding results were expressed in cmol(+)/kg (Jackson 1965).

Cation Exchange Capacity (CEC) Determination

The CEC was determined by extraction with ammonium acetate (Chapman 1965); CEC was calculated by summing the exchangeable cations (Ca^{2+} Mg^{2+} K^+ and Na^+) and expressing the result in centimoles of charge per kilogram [cmol(+)/kg] (Jackson 1965).

$$CEC = Ca^{2+} + Mg^{2+} + K^+ + Na^+ = [cmol(+)/kg] \qquad (1)$$

(Jackson 1965)

Exchangeable Sodium Percentage (ESP) Determination

The ESP, the fraction of sodium on the exchange sites is expressed as a percentage and was determined by using as:

$$\text{Exchangeable Na}^+ = \frac{\text{Na} + \text{Concentration} \times \text{CEC}}{100} \quad \text{-----------------} (2)$$

where,

Exch. Na^+ = concentration of exchangeable sodium [cmol(+)/kg]

CEC = cation exchange capacity [cmol(+)/kg].

Soil Organic Carbon (SOC) Determination

The SOC was determined by Walkley-Black method (Walkley and Black 1934). one gram (1g) of the air-dried soil sample was weighed and treated with 1N potassium dichromate ($K_2C_{r2}O_7$) and sulfuric acid (H_2SO_4) of ~96 - 98% w/w) was added to initiate oxidation. The mixture was swirled followed by titration with ferrous sulfate

($FeSO_4$) for determination of the amount of dichromate consumed. The amount of SOC was then calculated based on the amount of dichromate consumed:

$$SOC = \frac{V_1 - V_2 \times N \times 0.003 \times 100}{\text{weight of soil sample (g)}} \quad \text{------------ (3)}$$

(Walkley and Black 1934)

where,

V_1 = volume of $K_2Cr_2O_7$ used (mL)
V_2 = volume of FAS used (mL)
N = normality of $K_2Cr_2O_7$ (0.167N)
0.003 = conversion factor for carbon

Soil pH Determination

The Soil-pH was measured in a soil:water suspension, typically 1:2.50 soil:water ratio. The prepared soil sample was mixed with distilled water stirred for about 30 minutes to allow equilibration. The pH was then measured using a calibrated pH meter. The pH meter calibration was done using standard buffer solutions of pH 4, 7 and 10 (McLean 1982).

Spatial Interpolation Analysis

To visualize the distribution of each variable across the landscape, IDW interpolation was employed using the Spatial Analyst Tool in ArcGIS. IDW was chosen for its intuitive weighting mechanism, El-Seedy *et al.* (2023), wherein closer points have more influence on the interpolated surface than those farther away. The outcome was depicted in spatial thematic maps and discussed in terms of spatial patterns, gradients, hotspots and comparison with other variables (Figures 2a - 2h).

Linear Regression Analysis of Soil Fertility Indicators

Statistical analysis was conducted in Ms Excel where relationships of the soil fertility indices and their respective values were evaluated, compared and the degree of their contributions were determined in influencing the ESP dynamics and invariably to sodicity risks under different conditions. Scatterplot charts (ESP vs. CEC; ESP vs. soil pH) were generated from the relationships (Figures 3 - 5).

Multiple Regression Modelling for ESP Estimation

Statistical analysis was conducted in Ms Excel Data Analysis ToolPak tool confirm statistical significance value ($p < 0.05$), the regression model effectively predicts ESP variations, validating independent variable selection. The full specification was:

$$ESP = a + b(SOC) + c(CEC) + d(Soil\ pH) \quad \text{------------ (4)}$$

where,

a = (intercept) the baseline ESP value when SOC, CEC and Soil pH are zero
b = (slope for SOC) the change in ESP per unit increase in SOC.
c = (slope for CEC) the change in ESP per unit increase in CEC.
d = (slope for Soil pH) the change in ESP per unit increase in soil pH.

After running the regression, accuracy and validity of the regression model were checked. Observed and predicted values of ESP about the independent variables were compared and the model performance was assessed.

The model was revised by removing SOC and only two statistically significant CEC and Soil pH were considered to assess their relationship with the dependent variable

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ESP. The revised model's significance in terms p-values; *a, b, c, d* - regression coefficients; Adjusted R^2 were determined and compared. Tables of Analysis of variance (ANOVA) and regression coefficients for both original and revised models that showed the variables' relationships were generated, depicted and discussed (Tables 1 - 4).

Model Validation by k-fold Cross-Validation

Comparison between observed and predicted ESP was conducted after running the k-fold cross- validation:

$$L_i = \frac{1}{|V_i|} \sum_{(x_j y_j) \in V_i} l\left[\hat{f}_i(x_j), y_j\right] \text{ --------------- (5)} \quad \text{(Yan } et\ al. \text{ 2022)}$$

Given a dataset *D* of *N* samples and an integer *k*-folds):

where, *l* is a chosen loss function, the average cross-validation error is:

$$CV_k = \frac{1}{k}\sum_{i=1}^{k} L_i \text{ ------------------- (6)}$$

The model's performance was evaluated using both RMSE and R^2 metrics, thus:

RMSE was computed as a set of *n* observations $\{(xi, yi)\}$and corresponding predictions $\{\hat{y}_i\}$.

$$RSME_k = \sqrt{\frac{1}{n}\Sigma \times (y_i - \hat{y}i)^2} \text{ ------------- (7)} \quad \text{(Yan } et\ al. \text{ 2022 and Kumar } et\ al. \text{ 2023)}$$

The R^2 for each run were also computed and their accuracy calculated:

$$R_k^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y})^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \text{ -------------- (8)} \quad \text{(Yan } et\ al. \text{ 2022 and Kumar } et\ al. \text{ 2023)}$$

where,

yi = observed ESP values (actual values from dataset)

$\hat{y}_i$ = predicted ESP values (from regression)

$\overline{yi}$ = mean of observed ESP values

n = number of data points in each fold

k = number of folds (5 times of repetition).

The average performance metrics was averaged as RMSE and R^2 across all 5 (k) repetitions, their results are presented and discussed.

Results and Discussion

Spatial Interpolation and SOC - ESP Relationship

Figures 2a and 2b illustrate an inverse spatial relationship between soil organic carbon (SOC) and exchangeable sodium percentage (ESP). High ESP values (>25%) were observed at sampling points 3, 4, 5, and 6 (Figure 2b), which correspond to areas with low SOC concentrations (<1.5%) as shown in Figure 2a. This inverse correlation supports earlier findings that increased SOC can mitigate the negative effects of sodicity (Lal 2003), enhance microbial activity, and improve nutrient availability (Mahler *et al.* 2021).

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Chemically, SOC plays a critical role in modifying ESP behaviour through its influence on soil structure and cation mobility. According to Mahler *et al*. (2021), SOC improves soil aggregation and porosity, reducing clay dispersion and thus alleviating sodicity. Enhanced macro porosity facilitates the leaching of Na^+ from the root zone, effectively lowering ESP. Additionally, SOC-rich soils exhibit improved hydraulic conductivity, promoting Na^+ displacement and reducing its accumulation (Lal *et al.* 2003).

SOC also enhances the soil's cation exchange capacity (CEC). Jamaoui *et al.* (2025) report that SOC introduces negatively charged functional groups (e.g., carboxylic and phenolic), which preferentially bind divalent cations like Ca^{2+} and Mg^{2+} over Na^+. This selective binding promotes cationic balance and reduces Na^+ saturation on exchange sites. Conversely, in soils with low SOC, fewer exchange sites are available, allowing Na^+ to dominate and thereby increasing ESP (Lal *et al*. 2003; Jamaoui *et al.* 2025).

Furthermore, SOC supports microbial activity, which indirectly influences ESP dynamics. Microbial respiration produces CO_2 that dissolves in soil water, forming carbonic acid and slightly lowering soil pH. This process enhances Ca^{2+} solubility, facilitating Na^+ displacement from exchange sites (Mahler *et al.* 2021; Jamaoui *et al.* 2025). Such microbially driven carbon cycling thus contributes to ESP reduction and improved soil quality.

Overall, the spatial patterns observed underscore the ecological value of SOC in managing sodic soils. By improving aggregation, nutrient availability, and cation exchange processes, SOC not only lowers ESP but also reduces dependence on external soil amendments (Lal *et al.* 2003).

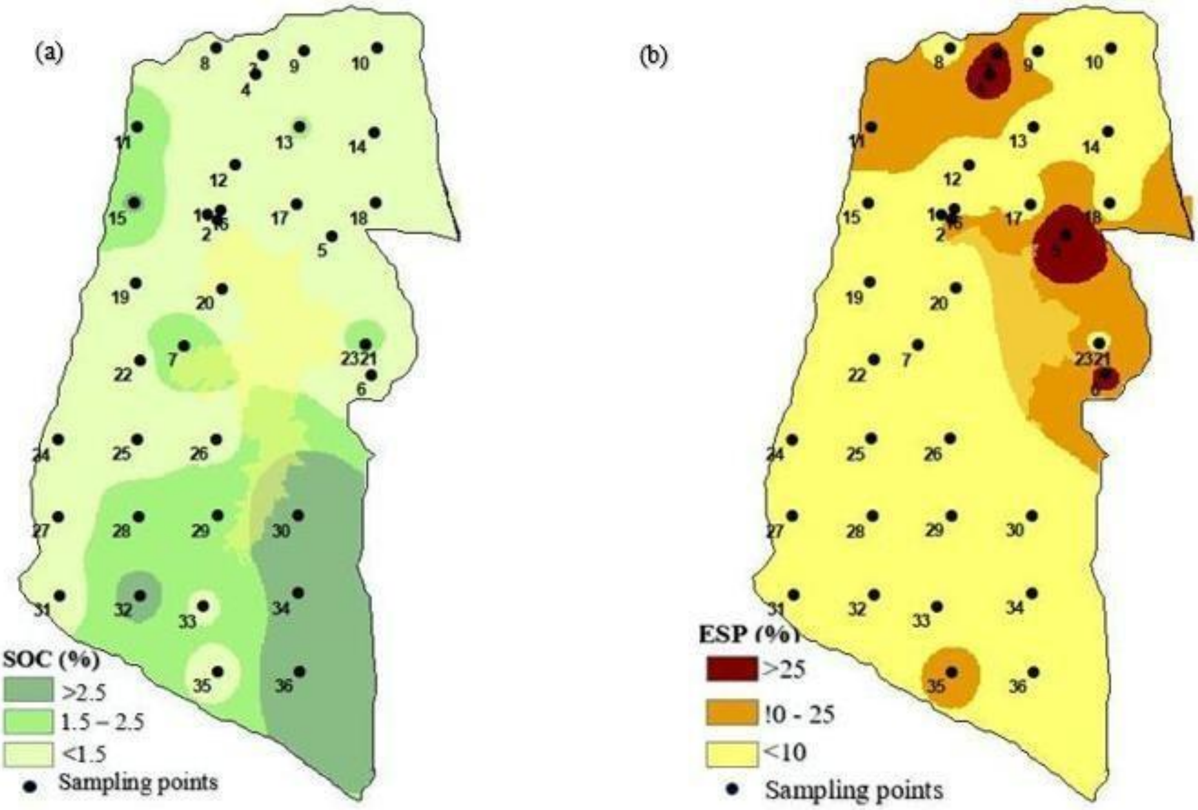

Figure 2: An IDW-interpolation output for (a) SOC (%) and (b) ESP (%) - showing sites with high quantity of (b) ESP (>25 and 10 – 25 (%) in points: 1, 2 16, 3, 4, 5, 6, 18, 21, 23, 30, 32, 34, 35 and 35 aligning with significant depletion of (a) SOC. This is an evident demonstration of inverse

relationship between the two variables (Lal *et al.* 2003).

The relationship between soil organic carbon (SOC) and exchangeable sodium percentage (ESP) is primarily indirect, as depicted in Figures 2a and 2b, where an inverse spatial correlation is evident. Previous studies have shown that SOC improves soil aggregation and porosity, which enhances water infiltration and reduces the fixation of exchangeable Na^+ in surface layers (Adane *et al.* 2019; Husein et al., 2021). In Figure 2a, areas with higher SOC concentrations (>2.5% and 1.5 - 2.5%) appear to buffer the detrimental effects of Na^+, thereby reducing the risks of soil dispersion.

Despite this observed trend, regression analysis (Table 2) revealed that SOC was not a significant predictor of ESP ($p = 0.962$, $p > 0.05$), suggesting that the direct relationship between these two variables is weak. This highlights the complex nature of soil sodicity, where SOC may influence ESP indirectly through improvements in soil structure and hydrological properties, but other factors may play a more prominent role in determining ESP levels.

Effects of Humic Substances on ESP

Humic substances released from organic matter influence exchangeable sodium (Na^+) mobility in the soil matrix, though their effect on ESP is indirect. As shown in regression models (Tables 1 and 2), SOC exhibited weak correlation with ESP, suggesting its limited predictive power for sodicity (Gosh *et al.* 2021). High Na^+ concentrations can deteriorate soil structure, reduce aeration, and inhibit microbial activity, limiting soil organic matter (SOM) decomposition (Mahler *et al.* 2021).

Moderate to high SOC levels (1.5 - 2.5% to >2.5%) at sampling points 7, 15, 30, 32, 34, and 36 (Figure 2c) show weak associations with ESP, indicating limited buffering against Na^+ effects. In contrast, low SOC areas (<1.5%) - which dominate the study area - coincide with higher Na^+ mobility and increased dispersion risks, as noted by (Phankamolsil *et al.* 2024).

SOC contributes to soil aggregation, porosity, and ion stabilization, but does not bind ESP as efficiently as clay particles. Its role in ESP retention is largely indirect, mediated by electrostatic interactions and improved soil structure (Jamaoui *et al.* 2025). In areas with higher SOC, soil aggregation prevents Na^+ dispersion, while low-SOC soils allow Na^+ mobility, increasing ESP levels (Adane *et al.* 2019). Additionally, the carboxyl and phenolic groups in SOC provide negative charge sites that preferentially bind divalent cations (Ca^{2+} and Mg^{2+}), reducing Na^+ retention and ESP (Bhunia *et al.* 2016; Jamaoui *et al.* 2025). Phankamolsil *et al.* (2024) found that SOC-rich soils buffer Na^+ effects, thus reducing sodicity risks. However, in low-SOC soils, Na^+ retention increases, worsening dispersion and ESP accumulation (Phankamolsil *et al.* 2024). Despite these findings, the weak correlation between SOC and ESP ($p = 0.962$, $p > 0.05$) suggests that SOC is not the primary factor controlling ESP.

Effects of Cation Exchange Capacity (CEC) on ESP

CEC (Figure 2) shows a clear interconnection with Na^+ dominance and nutrient availability, as evidenced by the distribution patterns of CEC and ESP across the study area. At point 5, where both CEC and ESP are at their lowest (<10 cmol(+)/kg and >25%, respectively), the two variables align. CEC reflects the number of negatively charged sites on soil particles (mainly clay and organic matter) that can absorb and exchange cations, including Na^+. Soils with high CEC (e.g., points 3, 4, 7, and 36 in Figure 2c) can better regulate ESP by providing more exchange sites for Na^+ binding (Saidi, 2012). High CEC soils retain more cations, including Na^+, but when Na^+ dominates these sites, ESP increases, disrupting soil structure and permeability (Chapman 1965; Saidi 2012). Conversely, low CEC soils struggle to bind Na^+ effectively, resulting in Na^+ leaching and reduced ESP, but the competition between Ca^{2+} and Mg^{2+} for exchange sites significantly influences Na^+ displacement, thus impacting ESP variations (Fitzpatrick *et al.* 1994; Adane *et al.* 2019).

In essence, while CEC is a key determinant of soil's ability to buffer against Na^+-induced dispersion, the presence of Na^+ in the exchange complex plays a critical role in ESP dynamics. Soils with high CEC may still exhibit low ESP if Na^+ is not a dominant cation, whereas low CEC soils struggle with Na^+ retention, affecting their ESP levels.

Another important chemical mechanism influencing the CEC - ESP relationship is the competitive exchange of cations based on valence and hydrated radius. As Chapman (1965) noted, divalent cations such as Ca^{2+} and Mg^{2+} are more strongly adsorbed than monovalent Na^+ due to their higher charge and smaller hydration shells. When Na^+ displaces these cations, inter-particle bonding

weakens, leading to clay dispersion, reduced infiltration, and increased ESP (Hailu and Mehari 202Stavi *et al.* (2021) observed that clay-rich soils with high CEC can initially buffer Na^+ more effectively; however, once Na^+ dominates exchange sites, these soils become prone to swelling and

dispersion. In contrast, sandy soils with inherently low CEC have limited buffering

capacity, and even small additions of Na^+ can cause a sharp rise in ESP (Chapman 1965).

Additionally, high CEC enhances a soil's buffering capacity by facilitating cation exchange. In locations such as sampling points 3, 4, 5, and 36 (Figures 2a and 2b), where both CEC and ESP were elevated (>25

cmol(+)/kg and 10 - 25%, respectively), high CEC may help moderate sodicity by enabling the replacement of Na^+ with Ca^{2+} or Mg^{2+} (Chapman 1965). Thus, while high CEC does not eliminate sodicity risks, it can increase soil resilience to Na^+-induced degradation.

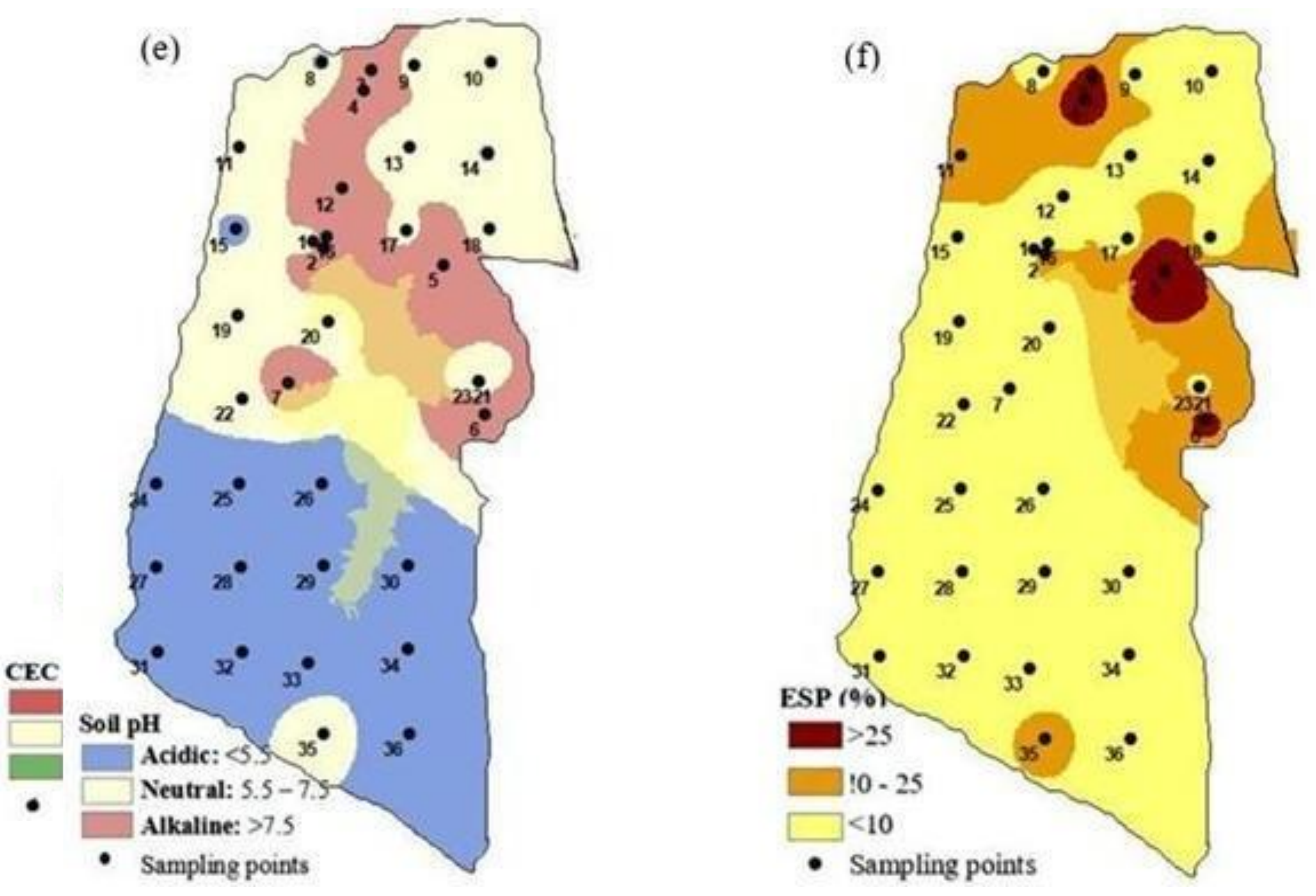

Figure 2: An IDW-interpolation output for (e) Soil pH and (f) ESP (%) layers – Soil pH regulates cation exchange dynamics and determines whether Na^+ in ESP remains bound or gets displaced. The interaction between both variables influences Na^+ mobility and soil dispersion behavior (Fitzpatrick *et al.* 1994).

Effects of Soil pH on ESP

Soil pH and ESP are closely interconnected, with elevated ESP often contributing to alkalization and associated soil constraints (Fitzpatrick *et al.* 1994; Gangwar *et al.* 2022). This interaction is typical of Aridisol soils in semi-arid regions, where low SOC and SOM exacerbate fertility limitations (Singh *et al.* 2023; Jamaoui *et al.* 2025). In this study, sites with alkaline pH (>7.5) corresponded to high ESP, reflecting weak Na^+ bonding at negatively charged clay surfaces, which enhances sodicity, nutrient imbalance, and dispersion risks (Trigunasih *et al.* 2019; Husnain *et al.* 2021; Ghosh *et al.* 2021). By contrast, acidic sites were characterized by lower ESP as Ca^{2+} and Mg^{2+} effectively displaced Na^+ from exchange sites, reducing sodicity and improving structural stability (McLean 1982; Husnain *et al.* 2024; Sani *et al.* 2024).

Thus, soil pH governs Na^+ mobility, ESP accumulation, and their combined effects on fertility and soil health (Dodd *et al.* 2013).

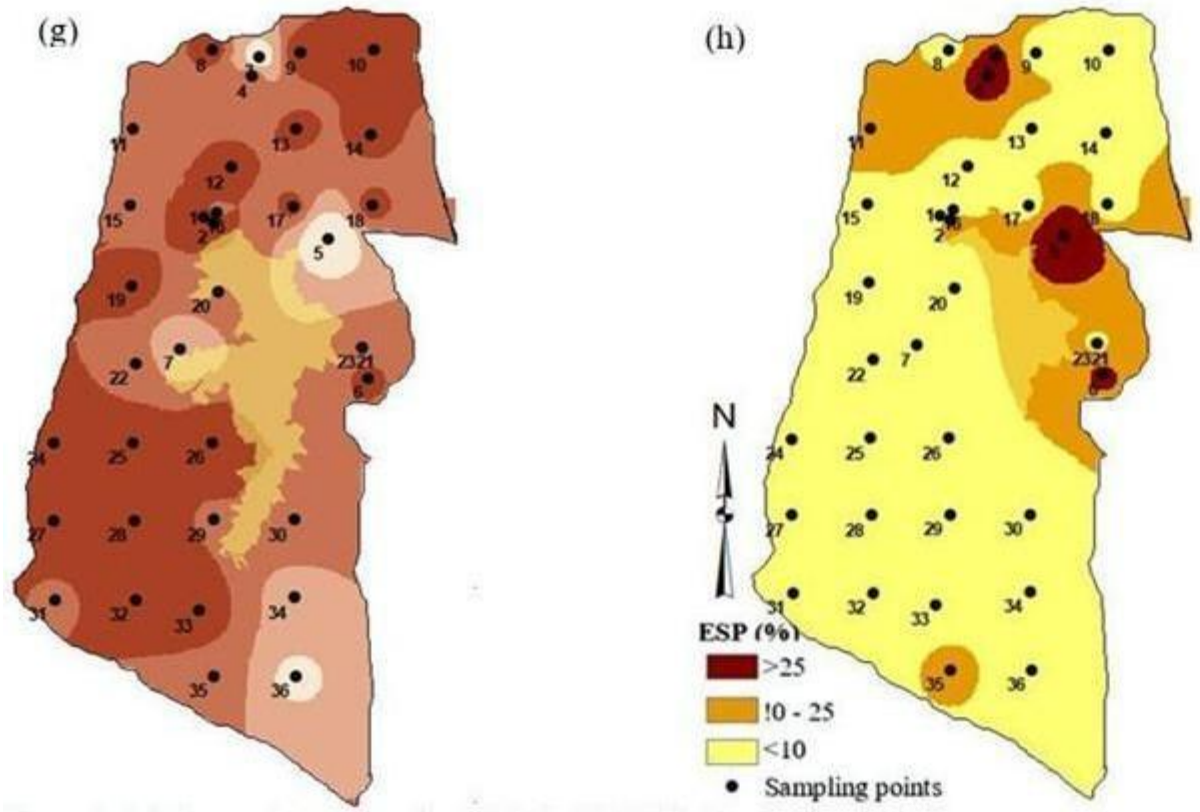

Figure 2: An overlay analysis output for (g) SOC, CEC & Soil pH layers - the chemical interactions of these variables provide critical insight into Na^+ retention, displacement and soil recovery potential. Their combined status determines whether a soil will accumulate Na^+ and degrade of buffer stress and support heathy plant growth (Hailegnaw *et al.* 2019 and Dhanushkodi *et al.* 2025).

Effects of SOC, CEC and pH on Soil Fertility

SOC, CEC, and pH jointly regulate ESP dynamics and soil fertility. SOC improves

CEC through negatively charged functional groups that preferentially bind Ca^{2+} and Mg^{2+}, thereby limiting Na^+ accumulation and sodicity (Adane *et al.* 2019; Husnain *et al.* 2021). Although high CEC enhances exchange capacity, ESP rises when Na^+ dominates the exchange complex, while Ca^{2+} and Mg^{2+} dominance stabilizes the soil even at high CEC (Dodd *et al.* 2013). Soil pH further modulates these interactions: under alkaline conditions, enhanced surface charge favours Na^+ adsorption and increases ESP, whereas under acidic conditions, competition from H^+ and Al^{3+} promotes Na^+ leaching and exchange, lowering ESP (Stavi *et al.* 2021). Together, SOC, CEC, and soil pH operate as key regulators of Na^+ retention, exchangeability, and mobility, thereby controlling ESP and shaping soil health and fertility.

Figure 2g shows that these variables act synergistically to mitigate the adverse effects of ESP, consistent with Dhanushkodi *et al.* (2025), who reported that optimal levels of SOC, CEC, and pH improve salt-affected soils and enhance crop productivity.

Soil pH, often termed the master regulator, dictates charge dynamics and cation solubility in relation to ESP. At high pH (> 7.5), typical of sodic soils, increased surface negativity favors Na^+ retention while reducing Ca^{2+} solubility, thereby elevating ESP. Conversely, at low pH (< 5.5), often induced by amendments or organic acids, Ca^{2+} and Mg^{2+} are released, displacing Na^+ from exchange sites and lowering ESP (Hailegnaw *et al.* 2019).

Linear Regression Analysis of Variables

The regression analysis showed that CEC had a positive but relatively weak influence on ESP, with a slope of 1.94 and R^2 of 0.31. This suggests that CEC accounts for only about 31% of ESP variation, implying that it contributes to sodicity but is not a dominant predictor. High-CEC soils, such as at points 3, 5, and 36, may accommodate more Na^+ without immediate sodicity effects if Ca^{2+} and Mg^{2+} dominate the exchange complex.

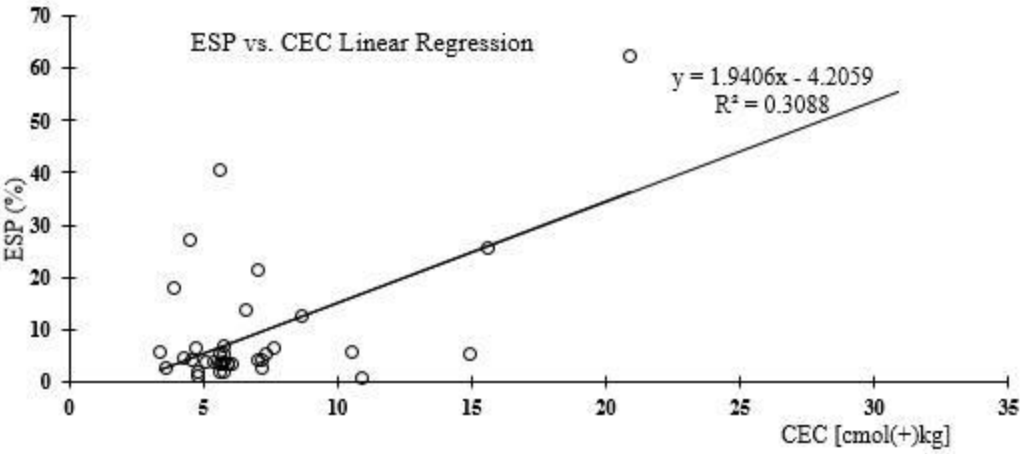

Figure 3: The relationship between ESP and CEC - the positive slope (y = 1.940) indicates a direct relationship between the two variables. As CEC rises, ESP also tends to increase, suggesting that soils with greater capacity to hold cations may accumulate more exchangeable Na^+ - especially when Na^+ dominates the exchange complexes.

However, where these cations are deficient, Na^+ accumulation increases ESP and risks structural degradation. In contrast, low - CEC soils are more sensitive, as even small Na^+ additions sharply elevate ESP, making them highly vulnerable to sodic degradation.

Thus, CEC plays a background buffering role in ESP dynamics but does not independently control sodicity.

By comparison, soil pH emerged as a stronger predictor, with a slope of 8.90 and R^2 of 0.47, explaining nearly 47% of the

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variation in ESP. The positive slope indicates that higher pH, typical of alkaline soils, promotes Na^+ retention and sodicity, requiring careful management to limit degradation risks (Mendieta-Mendoza *et al.* 2023).

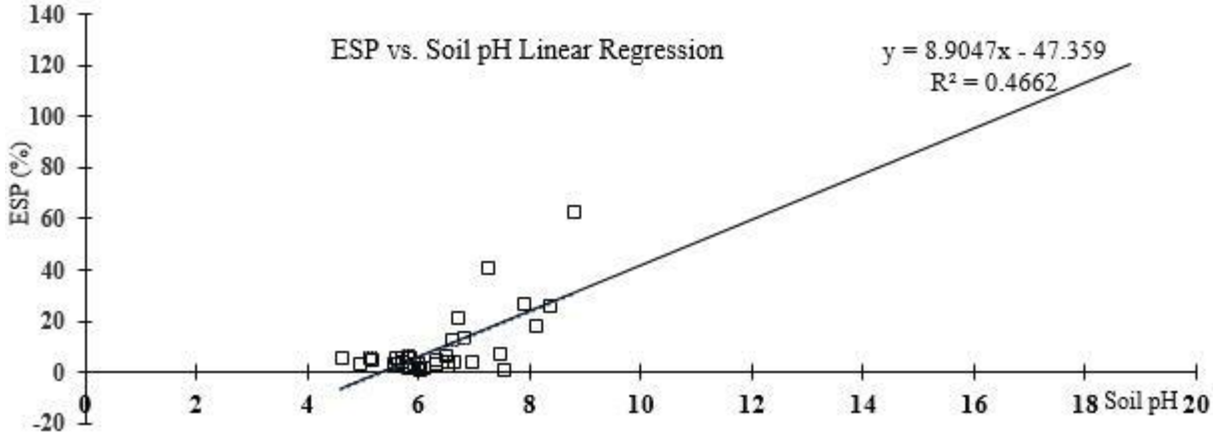

Figure 4: Relationship between ESP (%) and Soil pH - the original model shows strong correlation ESP ($R^2 = 0.4662$). The positive slope (8.9047) confirmed that higher pH increases ESP, sodicity risks are reinforced.

The negative intercept (-47.36) suggested that ESP would be negligible under strongly acidic conditions, reinforcing the role of low pH in mitigating Na^+ accumulation (Phankamolsil *et al.* 2024). These findings highlight that, while CEC contributes indirectly, soil pH is a more significant determinant of ESP and should be prioritized in models and management strategies for sodicity control.

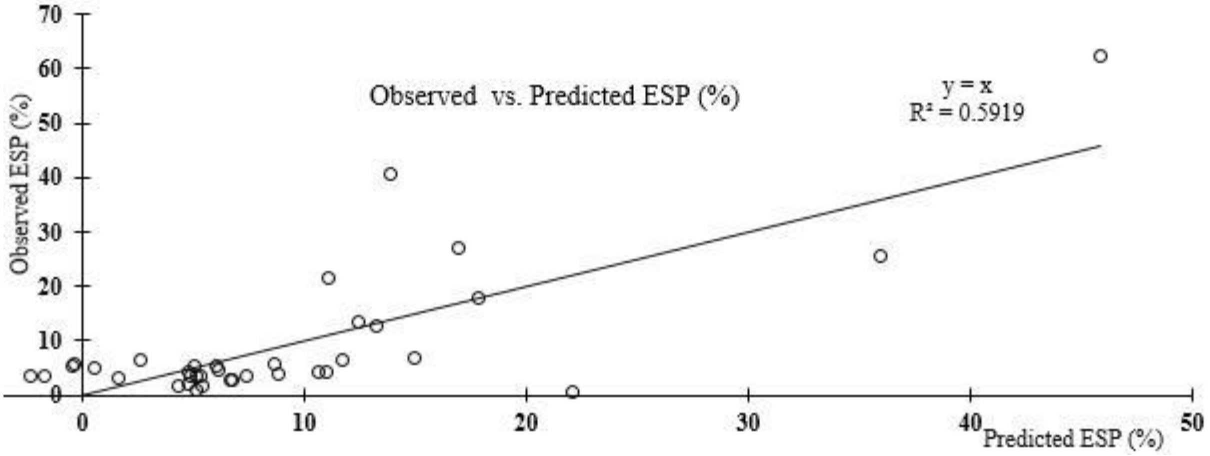

Figure 5: Relationship between observed and predicted ESP (%) - the equation y = x implies a perfect 1:1 correspondence, where predicted values match observed values exactly. The R^2 suggests that the regression model explains 59.19% of the variation in observed ESP, indicating moderate reliability and room for further optimization. This indicates a moderate predictive accuracy: the model performs reasonably well but leaves ~ 40% of ESP variability unexplained.

Multiple Regression Modeling of Variables

Multiple regression analysis assessed the combined influence of SOC, CEC, and soil pH on ESP. The model showed a moderate fit ($R^2 = 0.592$; Adjusted $R^2 = 0.554$), with CEC ($\beta = 1.41$, $p = 0.004$) and soil pH ($\beta = 6.62$, p

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= 0.001) emerging as significant positive predictors, while SOC (β = -2.70, $p > 0.05$) showed a weak, non-significant relationship. This suggests that while CEC and soil pH significantly influence ESP, SOC contributes little explanatory power and may weaken model precision. The model was statistically significant [$F(3,32) = 15.47$, $p < 0.05$].

Table 1: Analysis of variance (ANOVA) summary for the (original) multiple regression model estimating ESP using SOC, CEC and Soil pH.

	Df	SS	MS	F	Significance F
Regression	3	3264.0667	1088.02	15.4679	2.14862E-06
Residual	32	2250.8940	70.34		
Total	35	5514.9608			

The positive association between CEC and ESP aligns with Saidi (2012), reflecting Na^+ dominance in the exchange complex when Ca^{2+} and Mg^{2+} are deficient. Likewise, the positive relationship between soil pH and ESP supports earlier findings (Hailu and Mehari, 2021; Phankamolsil *et al.* 2024; Sani *et al.* 2024), attributable to Na_2CO_3 hydrolysis (Fitzpatrick *et al.* 1994; Mamedov *et al.* 2006). Although SOC is typically critical for soil health, its weak statistical effect here may reflect non-linear dynamics or confounding influences such as soil texture, climate, or nutrient status (Phankamolsil *et al.* 2024; Kramer *et al.* 2025).

A refined model excluding SOC improved stability (R^2 = 0.586; Adjusted R^2 = 0.561; SE = 8.31), with CEC remaining highly significant (β = 1.29, p = 0.004) but soil pH losing significance (β = 7.29, $p > 0.05$). This suggests that pH effects may depend on interactions with SOC or CEC. The refined model provided a more parsimonious fit [$F(2,33) = 23.40$, $p < 0.05$], underscoring CEC as the dominant predictor of ESP.

Table 2: Regression coefficients, standard errors, t-Stat, p-values (significance levels) for estimators of ESP for the original model.

	(a-d) Coefficients	Standard Error	t-Stat	p-value	Lower 95%
Intercept	-41.3778	11.8772	-3.4838	0.0015	-65.5709
SOC	-2.7017	4.1498	-0.6510	0.5197	-11.1547
CEC	1.4125	0.4620	3.0572	0.0045	0.4714
Soil pH	6.6225	1.8734	3.5350	0.0013	2.8064

This study has indicated that CEC and soil pH are significant predictors of ESP, while SOC does not show a significant influence in the initial model, prior to refinement (Table 2). The positive relationship between CEC and ESP aligns with previous study by Saidi (2012).

Similarly, the positive association between soil pH and ESP was consistent with the findings of Hailu and Mehari (2021), Phankamolsil *et al.* (2024) and Sani *et al.* (2024), which could attribute to the hydrolysis of Na_2CO_3 (Fitzpatrick *et al.* 1994, Mamedov *et al.* 2006 and Sani *et al.*

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2024). Although, soil pH is not always a direct indicator, other factors, such as the Na^+ Adsorption Ratio (SAR) most often played a vital role as well (Mamedov *et al.* 2006; Adane *et al.* 2019 and Husnain *et al.* 2024). The positive effect of CEC and soil pH may also be attributed to possibly increased CEC which could lead to a better nutrient retention, while a suitable soil pH range could enhance microbial activity and nutrient availability (Husnain *et al.* 2021).

The lack of a significant relationship between SOC and ESP was unexpected given the widely recognized importance of SOC. The SOC input, a favourable soil pH, neutral or slight alkaline and the accumulation of nutrients improved the biological status of the soil in promotion of microbial activities (Husnain *et al.* 2024). However, the study of Phankamolsil (2024), confirmed that high ESP levels brought about a reduction in SOC content and low concentrations of micronutrients in soils of Thailand.

Several factors could explain this result. First, the relatively low R^2 (0.592) suggests that other important factors not included in the model may be influencing ESP. These might include climate variable Kramer *et al.* (2025), nutrient levels Phankamolsil *et al.* (2024) soil texture (Fitzpatrick *et al.* 1994). Secondly, the relationship between SOC and ESP may be non-linear and therefore not captured by this linear model.

Since the relationship of SOC with the ESP was not statistically significant. The model was revised by removing the SOC from the modeling algorithm. The refined model considered CEC and soil pH as independent variables. The result demonstrated that the soil pH that was hitherto significant, now it lost its significance ($p = 4.36$, $p > 0.05$). Based on the F-statistical metrics, significant overall fit [$F(2,33) = 23.40$, $p < 0.05$)], became statistically insignificant. Soil pH $p > 0.05$ indicates that it no longer has a meaningful impact on ESP in the refined model. The implication for this is that its effect might have been dependent on SOC disrupted its significance or interaction with CEC. The CEC $p = 0.004$, $p < 0.05$ was highly significant and remains a strong predictor of ESP, showing a reliable effect even after SOC exclusion.

Despite the refinement with the exclusion of SOC, the model still showed moderate predictive strength, the loss of soil pH significance suggests that its role should be re-evaluated, possibly through interaction effects (CEC and soil pH). Removing SOC improved reliability, stability and predictive efficiency of the model, nevertheless affected variable significance. Furthermore, when revised model's F-statistics ($F = 23.40$) was compared to the previous model ($F = 15.46$) more merit of SOC removal became evident that the refined model fits better than before. The result of the revised model explains that 58.6% of the variance in ESP ($R^2 = 0.586$), the adjusted R^2 was 0.561, accounting for the reduced number of predictors and standard error was estimated as 8.31.

Table 3: Analysis of variance (ANOVA) summary for the (Refined) multiple regression model estimating ESP using CEC and Soil pH.

	Df	SS	MS	F	Significance F
Regression	2	3234.2522	1617.1261	23.3985	4.70654E-07
Residual	33	2280.7086	69.1124		
Total	35	5514.9608			

Furthermore, analysis of the regression coefficients of the revised model revealed statistically significant, positive relationships between CEC ($\beta = 1.29$, p =

0.004, $p < 0.05$) and ESP; but not significant between soil pH (β = 7.29, p = 4.36, $p > 0.05$) and the dependent variable ESP, hence the negative relationship. This confirms that CEC remains a key predictor in the overall modeling task. This implies that toil pH may not be a strong predictor of ESP when SOC is excluded. However, the explanatory power of the model (R^2 = 0.586) is comparable to the previous model which included SOC (R^2 = 0.592), suggesting that the removal of SOC did not substantially reduce the model's predictive ability. The adjusted R^2 values also show a similar trend with only a slight decrease in the revised model.

Secondly, the relationship between SOC and ESP may be non-linear and therefore not captured by the linear model (Ortom *et al.* 2014).

Table 4: Regression coefficients, standard errors, t-Stat, p-values (significance levels) for estimators of ESP for the refined model.

	Coefficients	Standard Error	t-Stat	p-value	Lower 95%
Intercept	-46.0382	9.3945	-4.9005	2.472E-05	-65.1515
CEC	1.2853	0.4150	3.0971	3.973E-03	0.4410
Soil pH	7.2945	1.5497	4.7070	4.362E-05	4.1416

Overall, these findings highlight CEC as the most reliable determinant of ESP, with soil pH exerting conditional influence and SOC showing limited predictive power. Future research should explore potential non-linearities, variable interactions, and additional soil properties to enhance model accuracy and inform management strategies for sodicity control.

K-Fold Cross-Validation

The predictive reliability of the revised regression model was evaluated using k-fold cross-validation. The model achieved a low RMSE of 2.91, reflecting relatively small prediction errors and indicating moderate-to-high accuracy in estimating ESP. The average R^2 was 0.567, showing that about 57% of ESP variability was explained, a level of predictive strength considered moderate but consistent across folds. Importantly, both CEC and soil pH retained predictive influence, reinforcing their stability as determinants of ESP.

Furthermore, the refined regression model and IDW-interpolated layers revealed consistent spatial patterns of sodicity risk. The close alignment between chemical theory, statistical predictions, and spatial outputs validates the regression approach and strengthens confidence in its application. Collectively, these results provide a reliable framework for ESP estimation and offer practical utility for sustainable land use, precision agriculture, and targeted soil management in semi-arid regions.

Conclusion

This study has demonstrated the efficacy of integrating geostatistical modelling and regression analysis to evaluate the spatial dynamics of soil fertility and sodicity in Aridisols of the Sudano-Sahelian savannah. Through the application of IDW interpolation in ArcGIS and statistical modelling in Microsoft Excel, the research revealed critical insights into the relationships between SOC, CEC, soil pH and ESP. While SOC exhibited an inverse spatial relationship with ESP, its statistical influence was weak, suggesting an indirect role mediated through soil structural improvements. In contrast, CEC emerged as the most significant predictor of ESP variability, with soil pH exerting a moderate effect. The refined regression model, validated through k-fold cross-validation, achieved improved predictive accuracy, underscoring the robustness of CEC as a diagnostic indicator for sodicity risk assessment. These findings highlight the importance of spatially explicit soil fertility evaluation in semi-arid environments, where sodicity poses a persistent threat to agricultural productivity and land sustainability.

By advancing a geospatial framework for soil health monitoring, this research contributes to precision agriculture and sustainable land management. It provides actionable insights for policymakers, extension services, and land users seeking to mitigate sodicity, optimize nutrient management, and enhance soil resilience in fragile ecosystems. Future studies should explore the integration of remote sensing data and machine learning techniques to further refine ESP prediction and support scalable soil reclamation strategies across diverse agroecological zones.

References

Adane, H., Gebrekidan and Kibret, K. (2019). Effects of Treatment Application Rates (Fym and Gypsum) on Selected Chemical Properties of Saline-Sodic Soils under Water Limited Condition in Eastern Lowlands Ethiopia. *Forestry Research and Engineering International Journal*, 3(3): 106-113, https://doi.org/10.15406/frei.2019.03.00086

Anderson, J.M. and Ingram, J.S.I. (1993). Soil Organic Matter and Organic Carbon. **In**: Tropical Soil Biology and Fertility, A hand Book of Methods (J.M. Anderson and J.S.I. Ingram, Eds)., CAB International, Wallingford, UK.

Bao, N., Wu, L., Ye, B., Yang, K. and Zhou, W. (2017). Assessing Soil Organic Matter of Reclaimed Soil from a Large Surface Coal Mine using a Field Spectroradiometer in Laboratory. *Geoderma*, 288: 47-55, https://doi.org/10.1016/j.geoderma.2016.10.033

Baballe, M.A., Abubakar, K.S., Fagge, I.I., Dahiru, M., Abubakar, F.U., Abubakar, U. and Ilyasu, A.S. (2022). Benefits and Challenges of Information Systems for Agricultural Management. *Global Journal of Research in Agriculture & Life Sciences*, 2(4): 15-25, https://doi.org/10.5281/zenodo.7030090

Bhunia, G.S., Shit, P.K. and Maiti, R. (2016). Spatial Variability of Soil Organic Carbon under Different Land-use Using Radial Basis Function (RBF). *Modelling Earth Systematic Environment*, 2(17): 1-8, https://doi.org/10.1007/s40808-015-0070-x

Chapman, H. D. (1965). Cation Exchange Capacity. **In:** C. A. Black (Ed.). Methods of Soil Analysis-Chemical and Microbiological Properties. *Agronomy*, 9: 891 - 901, https://dx.doi.org/10.2134/agronmonogr9.2.c7

de Oliveira, T.H.M., Painho, M., Santos, V., Sian, O. and Barriguinha, A. (2014). Development of an Agricultural Management Information System Based on

Open-source Solutions. *Proceedia Technology*, 16: 342-354, https://doi.org/10.1016/j.protcy.2024.10.100

Dhanushkodi, V., Nageswar, R., Anitha, R., Arulselvi, S., Periyar, R.D., Sangeetha, S., Karunakaran, V., Shenbagavalli, S., Amuthaselvi, G., Sangeetha, M., Rathika, S., Janaki, D., Anuratha, D., Thanga Hemavathy, A., Sabapathi, M. and

Yamunarani, K. (2025). Constraints in Salt-affected Soils and their Management through Biochar Application: A Review. *Applied Ecology and Environmental Research*, 23(1): 749 – 767, https://dx.doi..org/10.15666/aeer/2301_7497 67.

Dodd, K., Guppy, C.N., Lockwood, P.V. and Rochester, I.J. (2013). The Effect of Sodicity on Cotton: Does Soil Chemistry or Soil Physical Condition Have Greater Role? *Crop & Pasture Science*, 64: 806 – 815, https://doi.org/10.1071/cp13078

El-Seedy, M.E., El-Hamdi, K.H., El-Harty, H.M.F. and Saeed, M.A. (2023). Application of GIS Techniques and ASLE Program for Soil Fertility Assessment of Samannoud District, Gharbia Governorate, Egypt: *Egyptian Journal of Science*, 64(1): 119-134, https://doi.org/10.21608/ejss.2023.235525.1660

Fitzpatrick, R.W., Boucher, S.C., Naidu, R. and Fritsch, T. (1994). Environmental Consequences of Soil Sodicity. *Australian Journal of Soil Resources,* 32(5): 1069-1093, https//doi.org/10.1071/sr9941069

Gangwar, R.K., Makadi, M., Bresilla, B., Zain, M., Weldmichael, T.G., Demeter, I., Tancsics, A., Cserhati, M. and Szegi, T.A. (2022). Effects of Land uses and Soil types on Microbial Activity and Community Structure. *International Agrophysics*, 36: 323-336, https://doi.10.13545/intagr/1555096

Gebrehiwot, K. (2022). Soil Management for Food Security. *Natural Resources Conservation and Advances for Sustainabilit,* 61-71, https://doi.org/10.1016/B978-0-12-822976-7.00029-6

Ghosh, M., Ashiq, W., Vasava, H.B., Gamage, D.N.V., Patra, P.K. and Biswas, A. (2021). Short- term Carbon Sequestration and Changes of Soil Organic Carbon Pools in Rice under Integrated Nutrient Management in India. A*griculture*, 11(4): 348, https://doi.org/10.3390/agriculture11040348

Hailegnaw, N.S., Merci, F., Pracke, K., Szkova, J. and Tlustos, P. (2019). Mutual Relationships of Biochar and Soil pH, CEC and Exchangeable Base Cations in a Model Laboratory Experiment. *Journal of Soils and Sediment*, 19(5): 2405-2416, https://doi.org/10.1007/s11368-02264-z

Husein, H.H., Lucke, B., Baumler, R. and Sahwan, W. (2021): A Contribution to Soil Fertility Assessment for Arid and Semi-arid Lands. *Soil Systems*, 5(42): 1-13, https://doi.org/10.3390/soilsystems5030042

Hailu, B. and Mehari, H. (2021). Impacts of Salinity/Sodicity on Soil-Water Relations and Plant Growth in Dryland Areas: A Review. *Journal of Natural Sciences Research*, 12(3): 2224-0921, https://doi.org/10.7176/jnsr/12-3-01

Husnain, A., Farooq, Q., Sohail, S. S., Kumar, S., Zafar, A. and Rehman, B. (2024). Adaptability of Soil pH through Innovative Microbial Approach. *Current Research in Agricultural Sciences*, 8(2): 71-79, https://doi.org/10.18488/journal.68.2021.82.71.79

Jackson, M.L. (1965) Soil Chemical Analysis. Prentice Hall, Englewood Cliffs, 326-332

Jamaoui, I., Deldado-Iniesta, M.J., Sanchez, M.J.M., Sirvent C.P. and Lopez, S.M. (2025). Assessing Soil Organic Carbon in Semi-arid Agricultural Soils using UAV and Machine Learning: A Pathway to Sustainable Water and Soil Resource Management. *Sustainability*, 17(8): 3440, https://doi.org/10.3390/su17083440

Kumar, P., Priyanka, P., Jaya, D., Kala, U. and Dutt, V. (2023). Analyzing the Performance of Univariate and Multivariate Machine Learning Models in Soil Movement Prediction: A Comparative Study. *IEEE Access*, 11: 62368-62381, https://doi.org/10.1109/access.2023.3287851

Kramer, I., Peleg, N. and Mau, Y. (2025). Climate Change Shifts Risk of Soil Salinity and Degradation in Water-Scarce Regions. *Agricultural Water Management*, 307: https://doi.org/10.1016/j.agwat.2024.109223

Khan, M.Z., Islam, M.A., Sadiqui M. and Bhuiyan, M.M. (2019); Spatial Variability and Geostatistical Analysis of Selected Soil. *Bangladesh Journal of Scientific and Industrial Research,* 54(1): 55-66, https://doi.org/10.3329/bjsir.v54il.40731

Liu, Y., Zhu, L., Ding, L. and Sui, H. (2024). A Hybrid Sampling Method for Highly Imbalanced and Overlapped Data Classification with Complex Distribution. *Information Sciences,* 661(4): https://doi.org/10.1016/j.ins.2024.120117

Lal, R. (2003). Carbon Sequestration in Dryland Ecosystems. *Environmental Management,* 33(4): 528-544, https://doi.org/10.1007/s003-9110-9

Mamedov, A.I., Levy, G.J., Huang, C. and Norton, L.D. (2006). Effects of Sodicity and Soil Texture on Aggregate Stability of Semi-arid Soils. 14th International Soil Conservation Organization Conference. Water Management and Soil Conservation in Semi-Arid environments. Marrakech, Morocco.

Mahler, C.F., Svierzoski, D.S. and Bernerdino, C.A.R. (2021). Chemical Characteristics of Humic Substances in Nature. *Humic Substances*, https://doi.org/10.5772/intechopen.97414

McLean, E.O. (1982): Soil pH and Lime Requirement, **In:** Methods of Oil Analysis, Part 2. (Edited by A.L. Page, R.H. Miller and D.R. Keeney). *American Society of Agronomy*, Madison, Wisc: https://doi.org/10.2334/agronmonogr9.2.2ed.c12

Mendieta-Mendoza, A., Renteria-Villalobos, M., Randall, H., Róiz-Gomez and Rios-Lopez, M. (2023). Chemical Degradation of Agricultural Soil under Arid Conditions by the Accumulation of Potentially Toxic Elements and Salts. *Geoderma Regional*, 35: https://doi.org/10.1016/j.geodrs.2023.e00736

Naorem, A., Jayaraman, S., Dang, Y.P., Dalal, R.C., Sinha, N.K., Rao, C.S. and Patra, A.K. (2023). Soil Constraints in an Arid Environment - Challenges, Prospects and Implications. *Agronomy*, 13(1): 220, https://doi.10.3390/agronomy13010220

Njoku, J.D., Nnaji, A.O. and Iwuji, M.C. (2011). Spatial Analysis of Soil Fertility using Geographical Information Systems Technology. *An International Multidisciplinary Journal, Ethiopia*, 5(4): 511-524, https://doi.org/10.4314/afrrev.v514.69300

Ortom, T.G., Pringle, M.J., Kathryn, L.P., Ram, C.D. (2014). Spatial Prediction of Soil Organic Carbon Stock using a Linear Model of Coregionalization. *Geoderma*, 230(231):119-130, https://dx.doi.org/10.1016/j.geoderma.2014.04.016

Pal, D.K., Bhattacharyya, T., Sahrawat, K.L.

and Wani, S.P. (2016). Natural Chemical Degradation of Soils in the Indian Semi-arid Tropics and Remedial Measures. *Current Science*, 110(9): 1675-1682, https://doi.org/10.18520/cs/v110/i9/1675-1682

Phankamolsil, N., Tengprasert, T., Kheoruenromne, I., Phankamolsil, Y., Gilkes, R.J. and Sonsri, K. (2024). Interactive Influences of Salinity and Sodicity Levels on Depth-wise Soil Organic Matter and Micronutrient Elements in Thailand. *Environmental Resource Communities*, 6: https://doi.org/10.1088/2515-7620/ad3cbb

Stavi, I., Thevs, N. and Priori, S. (2021) Soil Salinity and Sodicity in Drylands: A Review of Causes, Effects, Monitoring and Restoration Measures. *Frontiers in Environmental Science*, (9): https://doi.org/10.3389/fenvs.2021.712831

Sani, S., Abdulkadir, A., Muhammad, M., Ibrahim, M., Nababa, A.S., Ubaidullah, A. and Suleiman, A. (2024). Assessment of Soil Salinity and Sodicity Status at Jibia Irrigation Project Katsina State Nigeria. *Life Sciences: An International Journal*,1(1): https://airccse.com/lsij/papers/1124lsij09.pdf

Saidi, D. (2012). Relationship between Cation Exchange Capacity and the Saline Phase of Cheliff Sol. *Agricultural Sciences*, 3(3): 434-443, https://doi.org/10.4236/as.2012.33051

Singh, V.K., Petel, V.K., Gupta, H., Patle, U. and Pandre, E. (2023). Soil Taxonomy: A Comprehensive Soil Classification System. In book: Current Research in Soil Science. AkiNik Publications New Delhi, 17-33, https://doi10.22271/ed.book.2421

Trigunasih, N.M., Narka, I.W. and Saifulloh, M. (2019). Measurement of Soil Properties for mapping soil fertility status. *International Journal of Design & Nature and Ecodynamics*, 18(6): 1381-1390, http://doi.org/10.1828/ijdne.180611

Walkley, A.J. and Black, I.A. (1934). Estimation of Organic Carbon by the Chromic Acid Titration Method. *Soil Science*, 37: 29-38, https://doi.org/10.1097/00010694-183401000-00003

Wang, K., Li, J., Zhou, Z. and Zhang (2023). Editorial: Soil Degradation and Restoration in Arid and Semi-arid Regions. *Frontiers in Environmental Science*, 11: https://doi.org/10.3389/fenvs.2023.1307500

Yan, T., Shen, S.L., Zhou, A. and Chen, X. (2022). Prediction of Geological Characteristics from Shield Operational Parameters by Integrating Grid Search and K-fold Cross-Validation into Stacking Classification Algorithm. *Journal of Rock Mechanics and Geotechnical Engineering*, 14(41): shttps://doi.org/10.2134/agronmonogr9.2.c7

Yang, F., An, F., Ma, H., Wang, Z., Zhou, X. and Liu, Z. (2016). Variations on Soil Salinity and Sodicity and its Driving Factors Analysis under Microtopography in Different Hydrological Conditions. *Water*, 8(227): https://doi.org/10.3390/w8060227