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Geospatial Analysis and Quadratic Regression Modelling of Soil Chemical Properties and Exchangeable Sodium in Aridisols of Sahel Savannah for Sustainable Soil Management

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ABSTRACT
Soil degradation, particularly sodicity, constitutes a major constraint to soil fertility and sustainable irrigation agriculture in semi-arid environments. Exchangeable sodium (Exch. Na^+) is a critical indicator of sodicity because its accumulation can impair soil structure, permeability and agricultural productivity. This study aimed to evaluate the spatial distribution of total exchangeable bases (TEB), soil organic carbon (SOC) and soil pH, and quantify their linear and nonlinear relationships with Exch. Na^+ in the Ajiwa Irrigation Scheme, Katsina State, Nigeria. Thirty-six surface soil samples (0–30 cm) were collected using a hybrid purposive-systematic sampling technique and analysed for exchangeable cations, TEB, SOC and soil pH. In ArcGIS 10.8, inverse distance weighting (IDW) was employed to generate spatial distribution surfaces, while second-order quadratic regression was used to model Exch. Na^+ using standardized TEB, SOC and soil pH. Model robustness was evaluated using leave-one-out cross-validation (LOOCV). Results revealed distinct spatial relationships, with high TEB zones [>15 cmol(+)/kg] coinciding with Exch. Na^+ hotspots [>25 cmol(+)/kg], particularly at sampling points 3, 5, 7 and 36. The quadratic regression explained 78.9% of the variation in Exch. Na^+ ($R^2 = 0.789$; adjusted $R^2 = 0.746$) and was highly significant ($F = 18.10$, $p < 0.001$). TEB was significant ($\beta = -0.738$, p = 0.033), while its quadratic component was highly significant ($\beta = 0.052$, $p = 0.002$), demonstrating a pronounced nonlinear threshold effect. The TEB–Exch. Na^+ quadratic relationship achieved $R^2 = 0.899$, compared with 0.521 for the linear relationship. LOOCV produced a low RMSE of 0.459, supporting predictive robustness. The study contributes an integrated geospatial-statistical framework for identifying sodicity hotspots and quantifying nonlinear soil-chemical relationships. It concludes that TEB is the dominant predictor of Exch. Na^+, while SOC and pH exert predominantly indirect spatial influences. Monitoring TEB thresholds, improving SOC and adopting appropriate sodicity-management practices are therefore essential for sustainable management of semi-arid irrigated soils.

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INTRODUCTION

Soil degradation phenomenon, particularly sodicity, represents a growing environmental challenge affecting soil fertility, water retention and ecosystem health in many semi-arid regions (Ouzemou *et al.* 2025). Among the key chemical indicators of sodic soil conditions is exchangeable sodium (Exch. Na^+, cmol(+)/kg), which can drastically impact soil structure, permeability and biological function (Adane *et al.* 2019 and Mendieta-Mendoza *et al.* 2023).

The study focuses on mapping the distribution of the key soil properties - total exchangeable bases [TEB, cmol(+)/kg], soil organic carbon (SOC, % and soil pH, *---Soil pH) - across the study area to determine how they spatially correlate with their dependent variable - the Exch. Na^+. Second-order polynomial regression model was employed to examine both linear and quadratic relationships between the variables - critical for guiding irrigation planning and sustainable soil management in drylands (Sani *et al.* 2024).

Soil salinization and sodicity pose significant constraint to agricultural productivity, Qadir *et al.* (2025), particularly in regions prone to chemical degradation due to intensive farming Demo (2025), poor drainage Yang *et al.* (2016), use of poor water quality for irrigation purpose Naorem *et al.* (2023), edaphic and climatic conditions of Aridisol soils of semi-arid zones (Kramer *et al.* 2025).

Considering the potentials of the area of study for supplying treated portable water and agricultural yields from irrigation farming activities to Katsina capital city as well as its neighbourhoods, the village is faced with depletion of vital soil chemical properties on its irrigable lands (Tuncay *et al.* 2021). This might be attributed to gradual accumulation of salts (Fitzpatrick *et al.* 1994 and Sani *et al.* 2024). It is a common phenomenon that causes hazardous impact on several irrigable sites of its counterpart in semi-arid regions of the world (Tuncay *et al.* 2021).

Both ecological and agronomical importance of Exch. Na^+ Fitzpatrick *et al.* (1994), the distribution and drivers of Exch. Na^+ remain poorly understood in many soil systems - especially where non-linear interactions play significant role (Pistocchi *et al.* 2017). Many past studies have relied on linear models or ignored spatial effects altogether, Chang *et al.* (2023), which can obscure critical relationships between soil chemistry variables, their respective chemical mechanisms that could guide and lead to sub-optimal land-use decision (Mohanavelu *et al.* 2021).

Furthermore, while techniques like IDW-interpolation have been widely adopted for mapping soil properties Gopal *et al.* (2015), Tuncay *et al.* (2016) and Subhasree *et al.* (2022), they are often applied in isolation, without integrating statistical modelling or validating how well interpolated surfaces correlate with predictive models. The disjointed approach may under-represent the true dynamics at play in soil systems affected by salinity or sodicity (Shahabi *et al.* 2016).

To address this multifaceted subject, the present study integrates both geospatial analysis, statistical modelling and predictive validation to examine how these key soil properties influence Exch. Na^+ at both local and landscape scales.

Therefore, the core research problem is: how do normalized TEB, SOC and Soil pH - along with their quadratic components - explain the spatial and statistical variation in Exch. Na^+ and to what extent can these relationships be reliably modelled and validated through integrated geostatistical and statistical approaches? By addressing this problem, the study seeks to: quantify both linear and non-linear effects of major soil properties on Exch. Na^+. Also provide validated prediction model through cross-validation. It as well offers spatial visualization that inform practical soil management decisions. Sodic soils are often overlooked in conventional land surveys despite their significant implications on land-use sustainability, crop performance and soil health. Exch. Na^+ (Sani *et al.* 2024).

This study is particularly justified for the following reasons: Firstly, the employed spatial interpolation of variables through IDW in ArcGIS supports visual interpretation, land planning and targeted interventions in Exch. Na^+ affected landscapes. Also, by including quadratic terms in the regression, the model captures curved and threshold effects that are common in soil chemical interactions but often ignored in linear-only models. And the application of cross-validation ensures that the model is not just statistically sound but also reliable for prediction and generalization.

MATERIALS AND METHODS

Description of the Study Area

This study was conducted in irrigated land around Ajiwa Dam within longitude 7°43′37.51″E, latitude 12°58′41.56″N and longitude 7°46′40.81″E, latitude 12°53′9.92″N. It covers an area of about 3,540 ha, located in Rimi Local Government Area of Katsina State in Nigeria's Sahel Savannah under semi-arid climatic zone (Baba, 2016; Ibrahim & Abdulkarim, 2017; Olaniyi *et al.*, 2025). Temperature values of 15.71°C; warmest month temperature >30°C. Rainfall is usually erratic, beginning in May to September. Evapotranspiration in the area is high and increases risks of salinity and sodicity (Baba, 2016). The soils are characterized as sandy, classified as Aridisols according to USDA Soil Taxonomy Classification Systems (Balasubramanian, 2017), primarily influenced by small holder irrigation practices, but faces soil degradation challenges that threatens productivity, characterized by low organic matter and high pH levels.

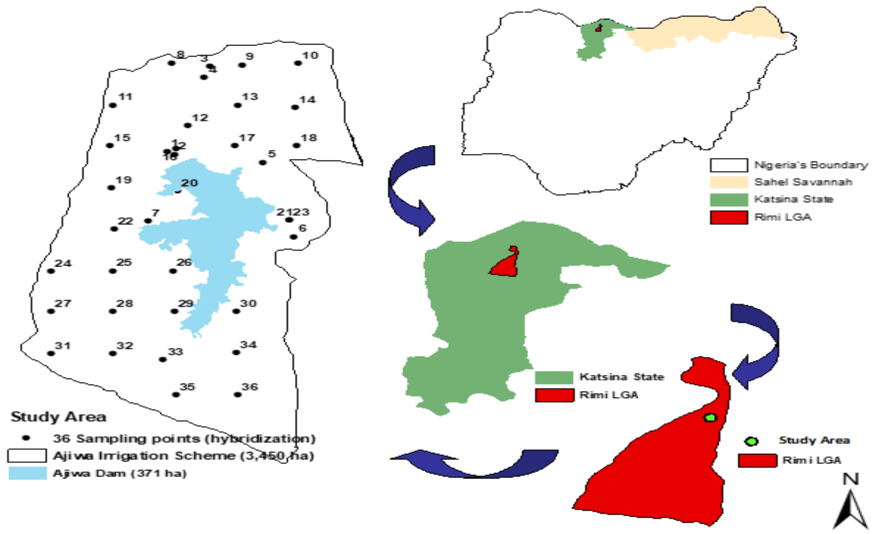


Figure 1**:** The study area in Katsina State lying in the Nigeria's Sudan-Sahel Savannah zone; the location of Rimi LGA within the state and the location of the study area. The extent of the study area showing the 36 soil sampling points collected by both purposive (1 - 7) and systematic (8 - 36): hybrid sampling technique (Liu *et al.* 2024)

Data Collection and Analysis Approach

Soil samples from seven purposive points were initially collected from areas where the whitish encrustation of salinization was evident in February, 2025. While in April, 2025, additional 29 samples were systematically collected at 1,500 m predetermined intervals. The sampling grids were generated in ArcGIS 10.8 software using its Create Fishnet Tool across the study area (Figure 1).

Total of 36 sampling points were generated and navigated to using an in-built GPS georeferencing with *Locus* and *Avenza* Maps applications for accurate coordinate points recording and tracking. Samples were collected by drilling and extraction using soil auger at depths specification of 0 – 30 cm using hybrid sampling technique (Figure 1) (Liu *et al.* 2024).

Soil Sample Preparation

The fresh soil samples were air-dried at room temperature. Dried soil was sieved through a 2 mm mesh. The sieved soil was homogenized to ensure uniformity in analysis. The sieved soil samples were ground to a uniform particle size. The grinded soil was weighed 2g of the prepared soil sample into a centrifuge tube.

Laboratory Analytical Procedures

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

The 30 mL of 1 M NH4OAc solution (pH 7.0) was added to the soil sample. The mixture was shaken using an orbital shaker at 200rpm for 30 minutes. The mixture was centrifuged at 3000 rpm for 10 minutes. The supernatant solution was filtered through a Whatman filter paper. The concentration of extracted cations was measured in the filtrate using Atomic Absorption Spectroscopy (AAS). Their corresponding results are expressed in [cmol(+)/kg] Jackson *et al.* 1958):

Determination of Exchangeable Sodium Ion (Exch. Na^{+})

The exchangeable Na^{+} can be expressed using the formular:

$$ExchNa^{+} = \frac{Na^{+} \times Concen\text{tr}ation \times CEC}{100}$$

(Jackson et al. 1958)

Where, Na^{+} concentration is measured Na^{+} concentration in soil extract [cmol(+)/kg] and CEC is the total exchangeable cations available in soil.

Determination of Total Exchangeable Bases (TEB)

In soil, the TEB refers to the sum of the exchangeable cations: Ca^{2+} Mg^{2+} K^{+} and Na^{+} held on soil particles. The standard laboratory procedure for its determination have been described earlier, as above. TEB was calculated by summing the exchangeable cations and expressing the result in centimoles of charge per kilogram [cmol (+)/kg] (Chapman 1965).

$TEB = ExchCa^{2+} + ExchMg^{2+} + ExchK^{+} + ExchNa^{+}$ = *[cmol (+)/kg]*. (Chapman 1965)

Determination of Soil Organic Carbon (SOC)

The SOC was determined by Walkley-Black (1934) method. The air-dried soil sample of 1.0g was weighed and treated with 1N potassium dichromate ($K_2Cr_2O_7$) and sulphuric acid (H_2SO_4) was added to initiate oxidation. The mixture was swirled followed by titration with ferrous sulfate ($FeSO_4$) for determination the amount of dichromate consumed. The amount of SOC was calculated based on the amount of dichromate consumed (Walkley-Black 1934):

$$SOC = \frac{v_1 - v_2 \times N \times 0.003 \times 100}{weight\ of\ soil\ Sample(g)}$$

where, v_1 is the volume of $K_2Cr_2O_7$ used (mL); v_2 = volume of FAS used (mL) N is normality of $K_2Cr_2O_7$ (0.167N) and 0.003 = conversion factor for carbon

Determination of Soil pH

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 and allowed to equilibrate. pH was then measured and calibrated pH meter.at a specific ratio of 1:2.50 soil water using standard buffer solutions before measurement (McLean 1982).

Laboratory Data into GIS Domain

Results from both field and laboratory were organized in a Microsoft Excel Spreadsheet and saved in GIS-compatible format for seamless integration. The data in Ms Excel spreadsheet containing the sampling points, latitude *(y)*, longitude *(x)*, Exch. Na^{+}, TEB, SOC and Soil pH was georeferenced by spatially joining their numerical values to geographic features for analysis in ArcGIS 10.8 software (Njoku *et al*. 2011).

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.* (2024), 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 - 2f).

Non-Linear Regression Analysis of Soil Properties

Statistical analysis was conducted in Ms Excel where relationships of the soil properties and their respective values were evaluated, compared and the degree of their contributions were determined in influencing the Exch. Na^{+} dynamics and invariably to sodicity risks under different conditions. Scatterplot charts (Exch. Na^{+} *versus* TEB; Residuals *versus* Predicted Exch. Na^{+} and Predicted Exch. Na^{+} *versus* TEB) were generated from the relationships (Figures 3 - 5).

Quadratic Regression Modelling for Exch. Na^{+} Prediction

Statistical analysis was conducted in Ms Excel Data Analysis ToolPak (Excel 2023) to account for both linear and curved relationships between Exch. Na^{+} and the key soil chemical properties, to the soil chemical properties, a second-order (quadratic) regression model was employed (Narvez-Ortiz *et al*. 2022). Independent variables - TEB, SOC and Soil pH were standardized using z-score normalization, scaled between 0 and 1 to eliminate scale biases and included in the model (James *et al*. 2023). The full specification was:

$$Exch.\ Na^{+} = a_1(TEB)^2 + a_2(SOC)^2 + a_3(Soil\ pH)^2 + b_1(TEB) + b_2(SOC) + b_3(soil\ pH) + c$$

where, Exch. Na^{+} is the predicted normalized variable; c is the intercept: the value of Exch. Na^{+} when all other variables are zero; TEB^2, SOC^2, Soil pH^2 are the squared quadratic values of the independent variables; used to model non-linear relationships; a_1, a_2 and a_3 are regression coefficients for quadratic terms: values will be determined by the analysis and represent the effect of each variable on Exch. Na^{+}; b_1, b_2 and b_3 = regression coefficients for linear terms.

Quadratic terms - TEB^2, SOC^2 and Soil pH^2 - were computed to capture potential curvilinear effects. Model performance was evaluated based on R^2, Adjusted R^2, F-statistics and p-values of individual predictors. The model was built and verified using Ms Excel standard statistical software, with a particular focus on the significance of the TEB and its quadratic term.

Analysis of variance (ANOVA) and regression coefficient tables for the model that showed the variables' relationships were generated, depicted and discussed (Tables 1 and 2).

Model Validation through Cross-Validation

James *et al.* (2023) reported that to ensure robustness of the regression model, Leave-One-Out Cross-Validation (LOOCV) was performed: The i-1 observation was excluded from 1 to 36. The regression model was built using the remaining 35 rows. The model was used to predict the left-out observation's Exch. Na^{+}. The squared error was computed as: $(\boldsymbol{y_i} - \hat{\boldsymbol{y}}_{-i})^2$ The process was repeated for all the 36 points. Given a dataset of *n* observation samples, the approximate values from the quadratic non-linear regression and predictions were used to estimate cross-validation performance. $RMSE_{LOOCV}$ was computed as a set of 36 observations and corresponding predictions:

$$RSME_{Loocv} = \sqrt{\frac{1}{n}\sum (y_1 = y)^2}$$

$$R^2 = 1 - \frac{\sum (y_1 - y)^2}{\sum (y = \bar{y})^2}$$

$$R^2 = 1 - \frac{SS_{\text{res}\,idual}}{SS_{total}}$$ (James *et al.* 2023)

where, y_i is the observed Exch. Na^+ values (actual values from dataset); $\hat{y}_i$ is the predicted Exch. Na^+ values (from regression); $\overline{yi}$ is the mean of observed values and *n* is the number of data points in each fold

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

RESULTS AND DISCUSSION

IDW Spatial Interpolation

The integrated IDW spatial interpolation provided a comprehensive visualization of soil chemical properties and their relationship with exchangeable sodium (Exch. Na^+) across the Ajiwa Irrigation Scheme. The continuous surfaces generated allowed clear identification of gradients, hotspots, and vulnerable zones, thereby offering both statistical and spatial insights into sodicity risks.

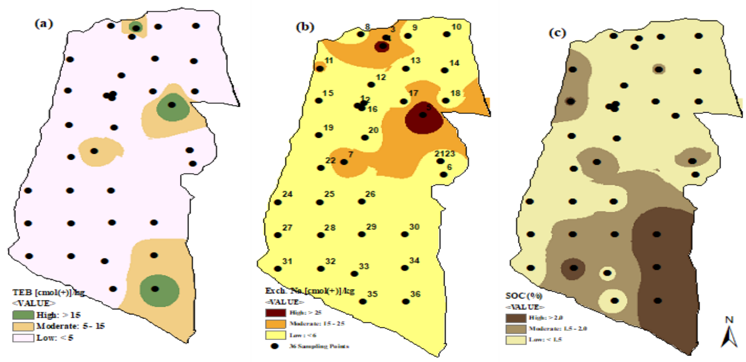


Figure 2a–c**:** IDW-interpolated maps of total exchangeable bases (TEB) and exchangeable sodium (Exch. Na^+). High TEB zones [>15 cmol(+)/kg] coincided with Exch. Na^+ hotspots [>25 cmol(+)/kg], confirming the quadratic regression where TEB^2 was significant (p = 0.011). This reflects cation competition: Na^+ dominates when Ca^{2+} and Mg^{2+} are depleted, dispersing soil structure and reducing drainage (Day and Ludeke, 1993; Iwasaki *et al.,* 2017; Wang *et al.,* 2020; Wang *et al.,* 2023).

Panel (a) depicts the distribution of total exchangeable bases (TEB), while panels (b–c) show Exch. Na^+ concentrations and SOC, respectively. High TEB zones [>15 cmol(+)/kg] coincided with elevated Exch. Na^+ hotspots [>25 cmol(+)/kg], particularly at points 3, 5, 7, and 36. This spatial overlap validates the regression findings, where TEB^2 was statistically significant (p = 0.011, $p < 0.05$), confirming a curvilinear relationship. The quadratic model captured the threshold effect: Exch. Na^+ increases sharply once TEB surpasses a critical level.

Chemically, this mechanism is explained by cation competition. Na^+, Ca^{2+}, Mg^{2+} and K^+ vie for exchange sites, but Na^+ dominates when divalent cations are depleted. High TEB with excessive Na^+ leads to dispersed soil structure, poor drainage, and sodicity hazards (Day and Ludeke, 1993; Iwasaki *et al.*, 2017; Wang *et al.*, 2020; Wang *et al.*, 2023). Conversely, low TEB sites [<5 cmol(+)/kg] aligned with low Exch. Na^+ [<6 cmol(+)/kg], reflecting stable soil aggregation. This duality underscores the importance of monitoring TEB thresholds in semi-arid soils.

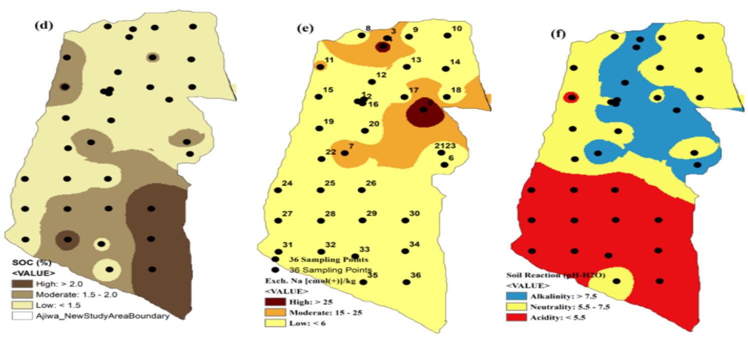


Figure 2d–f: IDW-interpolated maps of soil organic carbon (SOC), soil pH and Exch. Na^+. Low SOC areas (<1.5%) overlapped with higher Na^+, while moderate to high SOC buffered sodicity through aggregation and preferential binding of Ca^{2+} and Mg^{2+} (Iwasaki *et al.*, 2017; Sappor *et al.*, 2017; Rodriguez-Albarracin, 2023; Wang *et al.*, 2023). Alkaline soils (pH >7.5) coincided with high Na^+ due to carbonate precipitation, whereas acidic soils (<5.5) facilitated Na^+ displacement, confirming sodicity risks under alkaline conditions (Cemek *et al.*, 2007; Stavi *et al.*, 2021; Demo *et al.*, 2025)

Supporting studies confirm this mechanism. Wang *et al.* (2020) demonstrated that exchangeable base cations influence Na^+ retention and soil structure in long-term tea plantations, while Day and Ludeke (1993) emphasized that Na^+ dominance occurs when Ca^{2+} and Mg^{2+} are depleted. Thus, the IDW maps not only visualize these dynamics but also corroborate the regression outputs, strengthening the evidence base for soil management.

Panels (d–e) illustrate SOC distribution alongside Exch. Na^+. The spatial correlation is generally inverse: low SOC areas (<1.5%) overlapped with higher Na^+ concentrations, while moderate to high SOC (>1.5–2.0%) buffered sodicity risks. Although SOC was not statistically significant in the regression model, its indirect role is evident in the spatial patterns. SOC contributes to soil aggregation, porosity, water retention, and ion stabilization (Iwasaki *et al.,* 2017; Sappor *et al.*, 2017; Rodriguez-Albarracin, 2023; Wang *et al.*, 2023). High SOC soils provide functional groups (carboxyl, phenolic) that preferentially bind Ca^{2+} and Mg^{2+}, thereby displacing Na^+ and reducing sodicity. SOC also enhances microbial activity and root exudation, further stabilizing aggregates and limiting Na^+ mobility (Day and Ludeke, 1993).

In contrast, SOC-poor soils lack organic binding, allowing Na^+ to accumulate freely at exchange sites, worsening dispersion and infiltration problems. This was evident in the IDW maps, where low SOC zones coincided with high Exch. Na^+ concentrations. Sappor *et al.* (2017) demonstrated that organic amendments such as poultry manure and biochar increased SOC and reduced ESP below sodicity thresholds in Ghanaian soils, highlighting the practical importance of SOC management.

Thus, while SOC's direct statistical effect was weak, its indirect buffering role is critical. The IDW maps provide spatial confirmation of this mechanism, reinforcing the need to enhance SOC through organic amendments in semi-arid irrigation systems.

Panels (f) show soil pH alongside Exch. Na^+. Alkaline sites (pH >7.5) aligned with higher Na^+ concentrations, consistent with carbonate precipitation and reduced Ca^{2+} solubility. Acidic soils (pH <5.5) favored Na^+ displacement due to increased H^+ activity. Although soil pH was not statistically significant in the regression, its influence is evident in spatial patterns: high pH zones overlapped with elevated Exch. Na^+, supporting sodicity risks under alkaline conditions.

This mechanism is well documented. Cemek *et al.* (2007) found strong correlations between high pH and elevated ESP in sedimentary soils, while Stavi *et al.* (2021) emphasized that alkaline pH enhances Na^+ accumulation in drylands, particularly under irrigation. Demo *et al.* (2025) noted that at neutral pH (5.5–7.5), Na^+ exists primarily in exchangeable form, competing with other cations, whereas at high pH, Na^+ reacts with Na_2CO_3, increasing sodicity. The IDW maps confirm these dynamics: alkaline zones coincided with high Exch. Na^+, while acidic zones showed reduced Na^+ retention. Thus, soil pH, though statistically secondary, plays a significant indirect role in sodicity risk.

Taken together, the IDW maps and regression analysis converge on a consistent conclusion: sodicity risk in Nigerian Aridisols is primarily governed by exchange capacity thresholds, with SOC and Soil pH contributing indirect buffering effects. The spatial interpolation validates the statistical findings, highlighting critical hotspots and providing a practical framework for targeted soil management interventions.

High TEB zones with excessive Na^+ represent the greatest risk, requiring careful monitoring and management. SOC enhancement through organic amendments can buffer sodicity, while pH management (e.g., through gypsum application or improved drainage) can mitigate Na^+ retention. The integration of geospatial and statistical approaches thus provides a robust, validated framework for sustainable soil management in semi-arid irrigation systems.

Quadratic Regression Modelling

The quadratic regression model was employed to evaluate the influence of soil fertility indices—total exchangeable bases (TEB), soil organic carbon (SOC), and soil pH - on Exch. Na^+. The model achieved a strong fit (R^2 = 0.789; Adjusted R^2 = 0.746), indicating that nearly 79% of the variation in Exch. Na^+ was explained by the predictors (Table 1).

The ANOVA confirmed the model's statistical significance (F = 18.10, p < 0.001), validating its robustness and predictive adequacy. These results underscore the importance of including quadratic terms in soil chemistry modelling, as linear-only models often fail to capture threshold effects and curvilinear dynamics (James *et al.,* 2023; Rodriguez-Albarracin *et al.,* 2023). The regression coefficients (Table 2) revealed that TEB (linear term) was significant (β = –0.738, p = 0.033), showing a negative linear relationship with Exch. Na^+, while TEB^2 (quadratic term) was highly significant (β = 0.052, p = 0.002), confirming a strong curvilinear effect.

Table 1: Analysis Of Variance (ANOVA) Summary For The Quadratic Regression Model Predicting Exchangeable Sodium (Exch. Na^+) Using Total Exchangeable Bases (TEB), Soil Organic Carbon (SOC), And Soil Ph. The Model Was Statistically Significant (F = 18.10, P < 0.001), With Regression Sum Of Squares (SS = 161.27) Explaining Most Of The Variation Compared To Residual SS = 43.06. Overall, the Predictors Accounted For 77.9% of the Variability in Exch. Na^+ (R^2 = 0.789), Confirming the Robustness of the Quadratic Specification

	Df	SS	MS	F	Significance F
Regression	6	161.2652	-0.5220	18.1015	1.2899
Residual	29	43.0598	1.4848		
Total	35	204.3251			

Source**:** Generated using *Ms Excel* 2023

In contrast, SOC and soil pH (both linear and quadratic terms) were not statistically significant (p > 0.05), suggesting limited direct influence on Exch. Na^+ under the studied conditions. This finding is consistent with earlier work in Nigerian Aridisols, where cation exchange capacity (CEC, closely related to TEB) was identified as the strongest predictor of sodicity indices such as ESP (Ibrahim *et al.,* 2020; Sani *et al.,* 2024). The graphical outputs further illustrate these relationships. Figure 3a shows a moderate linear correlation between Exch. Na^+ and TEB (R^2 = 0.52), indicating that while TEB is a driver, the relationship is not purely linear.

Figure 3b (Residuals vs. Predicted Exch. Na^+) indicates weak curvature (R^2 = 0.12), suggesting that residuals are largely random and the model does not suffer from systematic bias. Most importantly, Figure 3c (Predicted Exch. Na^+ vs. TEB) demonstrates a strong quadratic fit (R^2 = 0.90), highlighting

Table 2: Regression Coefficients and Significance Levels for Predictors of Exch. Na^+. The Quadratic Term Of Total Exchangeable Bases (TEB^2) Was Highly Significant (*P* = 0.002), While The Linear Term Of TEB Also Showed Significance (*P* = 0.033). SOC and Soil Ph (Both Linear and Quadratic Terms) Were Not Statistically Significant (*P* > 0.05), Indicating Limited Direct Influence. Overall, the Model Confirms TEB as the Dominant Predictor of Exch. Na^+ under Semi-Arid Aridisol Conditions

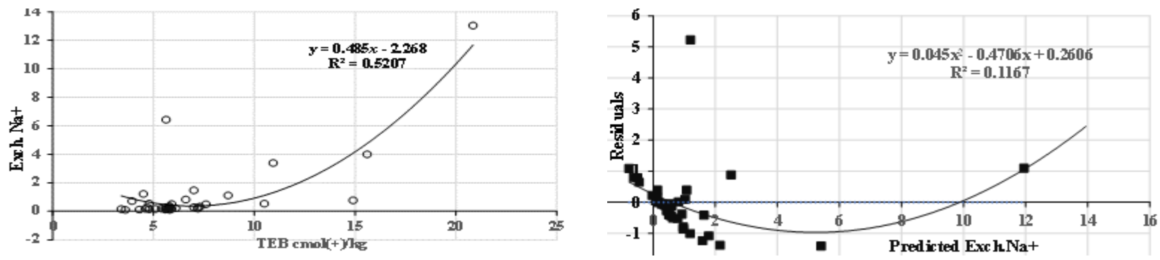
	Coefficient	Standard Error	t-Stat	p-value	Lower 95%
Intercept	-6.1836	11.8764	-0.5220	0.6065	-30.4737
TEB	-0.7381	0.3290	-2.2433	0.0326	-1.4111
SOC	1.6417	1.8310	0.8965	0.3773	-2.1032
Soil pH	1.9495	3.7763	0.5162	0.6095	-5.7740
TEB^2	0.0524	0.0155	3.3828	0.0020	0.0207
SOC^2	-0.2982	0.9009	-0.9203	0.3649	-2.6717
Soil pH^2	-0.0877	0.2917	-0.3007	0.7657	-0.6844

Source: Generated using *Ms Excel* 2023

TEB's dominant role in shaping Exch. Na^+ dynamics. The curve shows that Exch. Na^+ increases disproportionately at higher TEB levels, reflecting threshold effects in sodium accumulation. This validates the chemical mechanism whereby Na^+ competes with Ca^{2+} and Mg^{2+} for exchange sites, and once TEB surpasses a critical threshold, Na^+ dominance leads to soil dispersion and poor drainage (Day & Ludeke, 1993; Wang *et al.,* 2020).

The implications of this relationship are significant. At low TEB levels [< 5 cmol(+)/kg], Exch. Na^+ remains low, supporting stable soil aggregation and fertility. However, beyond a threshold, Exch. Na^+ rises sharply, leading to sodicity risks. This curvilinear behaviour is consistent with findings in semi-arid soils globally, where exchange capacity strongly governs sodicity hazards (Qadir *et al.,* 2025; Stavi *et al.,* 2021). SOC and soil pH, though important for soil health, do not significantly predict Exch. Na^+ in this dataset. Their influence is indirect: SOC enhances aggregation and water retention, buffering Na^+ effects (Iwasaki *et al.,* 2017; Sappor *et al.,* 2017), while alkaline soil pH (> 7.5) favours Na^+ retention through carbonate precipitation (Cemek *et al.,* 2007; Demo, 2025). Yet statistically, their contributions were weak compared to TEB.

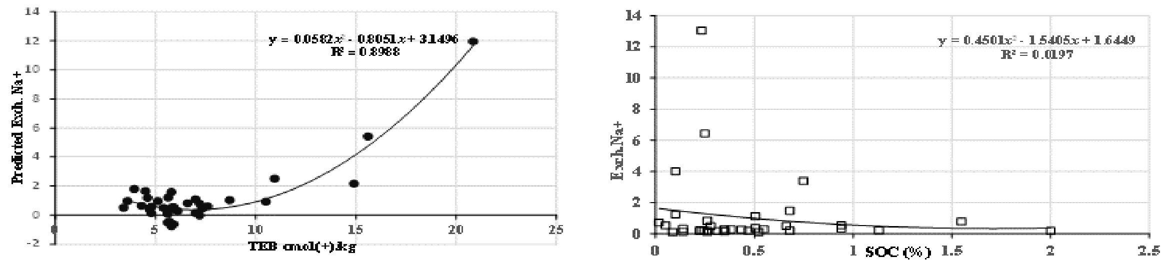
The quadratic regression thus confirms that TEB is the critical fertility index governing sodicity risk in these soils. The curvilinear relationship suggests that management strategies must monitor TEB thresholds carefully. Excessive TEB, dominated by Na^+, leads to soil structural collapse, poor infiltration, and reduced productivity.



A B

Figure 3a and 3b: Exch. Na^+ vs. TEB and Residuals vs. Predicted Exch. Na^+ Panel (a) shows a moderate linear correlation (R^2 = 0.52) between Exch. Na^+ and TEB, reflecting Na^+ competition with Ca^{2+} and Mg^{2+} at exchange sites, with accumulation intensifying beyond TEB thresholds (Day & Ludeke, 1993; Wang *et al.,* 2020). Panel (b) depicts residuals against predicted Exch. Na^+, with weak curvature (R^2 = 0.12) and largely random distribution, confirming that the quadratic model captures most systematic variation while leaving only noise unexplained (James *et al.,* 2024)

This reinforces the need for interventions such as balanced fertilization, gypsum application, and organic amendments to maintain Ca^{2+} and Mg^{2+} dominance at exchange sites (Sappor et al., 2017; Wang *et al.,* 2023). In Ghanaian soils, poultry manure and biochar have been shown to reduce ESP below sodicity thresholds, highlighting the potential of organic inputs to buffer Na^+ effects (Sappor *et al.,* 2017). Similar strategies could be adapted for Nigerian savannah soils.



C D

Figure 3c and 3d: Predicted Exch. Na^+ vs. TEB and Exch. Na^+ vs. SOC; (c) illustrates the quadratic regression curve of predicted Exch. Na^+ against TEB, showing a strong fit (R^2 = 0.90) and mechanistically validating sodicity thresholds where Na^+ dominance leads to soil dispersion (Qadir *et al.,* 2025; Stavi *et al.,* 2021). Panel (d) presents Exch. Na^+ vs. SOC, with a weak correlation ($R^2 < 0.20$) consistent with SOC's indirect role in buffering Na^+ through aggregation and ion stabilization rather than direct prediction (Iwasaki *et al.*, 2017; Sappor *et al.*, 2017).

The quadratic regression curve in Figure 3c demonstrates a strong curvilinear relationship between predicted Exch. Na^+ and TEB, with $R^2 = 0.8988$**.** This high coefficient of determination indicates that nearly 90% of the variation in Exch. Na^+ is explained by TEB alone when modeled quadratically. Mechanistically, this reflects the competition among cations at exchange sites: at low TEB levels [< 5 cmol(+)/kg], Na^+ remains limited, but as TEB increases, Na^+ accumulation rises disproportionately once Ca^{2+} and Mg^{2+} are depleted. This threshold behaviour is consistent with sodicity processes described in semi-arid soils (Day & Ludeke, 1993; Qadir *et al.*, 2025). The curve validates the chemical mechanism whereby excessive Na^+ dominance leads to soil dispersion, poor infiltration, and structural collapse.

Leave-One-Out Cross-Validation (LOOCV)

To test the robustness of the quadratic regression model, LOOCV was applied to the 36 soil samples. Each observation was excluded in turn, the model rebuilt on the remaining 35, and the excluded value predicted. The squared errors were averaged to estimate predictive accuracy (James *et al.*, 2023). This method is widely used in small datasets as it maximizes data use while minimizing bias (Rodriguez-Albarracin *et al.*, 2023).

The results confirmed predictive adequacy. Based on the revised ANOVA outputs (Table 1), the residual sum of squares (SSresidual = 43.06) and total sum of squares (SS_{total} = 204.33) yielded $RMSE_{LOOCV}$ = 0.459, a relatively low error. This complements the model's high explanatory power (R^2 = 0.789) and the strong quadratic fit in Figure 3c (Predicted Exch. Na^+ vs. TEB, R^2 = 0.90)**.** Together, these metrics demonstrate that the model is statistically robust and generalizable.

Residual analysis (Figure 3b) further supports this conclusion. Although residuals showed weak curvature (R^2 = 0.12), their largely random distribution indicates that predictors capture most of the variation in Exch. Na^+, leaving only noise unexplained (James *et al.*, 2024). The consistency between the LOOCV error and residual behaviour strengthens confidence in the model's adequacy.

From a soil management perspective, these findings highlight the importance of monitoring TEB thresholds. The quadratic regression revealed that Exch. Na^+ rises disproportionately at higher TEB levels (Figures 3a and 3c), and the low $RMSE_{LOOCV}$ confirms this pattern across all sampling points. This aligns with studies in semi-arid soils where exchange capacity governs sodicity risks (Qadir *et al.*, 2025; Stavi *et al.*, 2021). It also supports interventions such as gypsum application, balanced fertilization, and organic amendments to maintain Ca^{2+} and Mg^{2+} dominance, thereby buffering against Na^+ accumulation (Sappor *et al.*, 2017; Wang *et al.*, 2020).

This study demonstrated that exchangeable sodium (Exch. Na^+) dynamics in Nigerian Aridisols are primarily governed by total exchangeable bases (TEB) and its quadratic term. Regression analysis confirmed TEB (p = 0.033) and TEB^2 (p = 0.002) as significant predictors, with a strong quadratic fit (R^2 = 0.90) compared to the moderate linear correlation (R^2 = 0.52). Validation through LOOCV yielded a low error (RMSE = 0.459) and random residuals (R^2 = 0.12), confirming the model's robustness. Mechanistically, these results highlight sodicity thresholds, where Na^+ dominance at exchange sites leads to soil dispersion and poor drainage, consistent with findings in semi-arid soils (Day & Ludeke, 1993; Qadir et al., 2025; Stavi et al., 2021).

CONCLUSION

The IDW spatial interpolation layers reinforced these statistical findings by mapping the distribution of TEB, SOC, soil pH, and Exch. Na^+ across the study area. Hotspots of high TEB coincided with elevated Exch. Na^+ concentrations (points 3, 5, 7 and 36), validating the quadratic regression curve and threshold behaviour. Conversely, areas of low SOC (< 1.5%) overlapped with higher Exch. Na^+ zones, confirming SOC's indirect buffering role in soil aggregation and Na^+ mobility (Iwasaki et al., 2017; Sappor et al., 2017). Similarly, alkaline pH sites (> 7.5) aligned with higher Exch. Na^+ values, supporting the mechanism of carbonate precipitation and Na^+ retention (Cemek *et al.*, 2007). Together, the regression and spatial analysis provide a comprehensive framework: the regression quantifies the strength and form of relationships, while the IDW maps visualize their spatial manifestation. This integrated approach offers a validated tool for predicting sodicity risks and guiding sustainable soil management strategies under semi-arid conditions, emphasizing the need to monitor TEB thresholds and strengthen SOC through organic amendments.

REFERENCES

Adane, H., Gebrekidan & 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 Internationa Journal.* 3(3): 106-113, http://doi.org/10.15406/frei.2019.03.00086

Baba, H. (2016): Soil organic and Carbon Potential in Nigeria. *Geoderma*, 271: 202–215, http://doi.org/10.1016/j.geoderma.2016.02.015

Balasubramanian, A. (2017): Soil Taxonomy and Classification. *Technical Report*, http://doi.org/10.13140/rg.2.2.15832.08964

Chang, N., Jing, X., Zeng, W., Zhang, Y., Li, Z., Chen, D., Jiang, D., Zhong, X., Dong, G. & Liu, Q. (2023): Soil Organic Carbon Prediction Based on Different Combinations of Hyperspectral Feature Selection and Regression Algorithm. *Agronomy*, 13(7): http://doi.org/10.3390/agronomy13071806

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

Cemek, B., Guler, M., Kilic, K., Demir, Y. & Arslan, H. (2007): Assessment of Spatial Variability in some Soil Properties as Related to Soil Salinity and Alkalinity in Bafra Plain in Northern Turkey. *Environmental Monitoring & Assessment.*, 124: 223-234, http://doi.org/10.1007/s10661-006-9220-y

Day, A.D. & Ludeke, K.L. (1993): Plant Nutrients in Environments. *Springer-Verlag,* Berlin Heidelberg.

Day, P.R., & Ludeke, K.L. (1993): How Do Sodic Soils Behave – the Effects of Sodicity on Soil Physical Behavior. *Soil Research,* 31(1): 761–777, https://doi.org/10.1071/SR9930761

Demo, A.H., Gemeda, M.K., Abdo, D.R., Guluma, T.N. & Adugna, D.B. (2025): Impact of Soil Salinity, Sodicity and Irrigation Water Salinity on Crop Production and Coping Mechanism in Areas of Dryland Farming. *Agrosystems, Geosciences & Environment* http://doi.org/10.1002/agg2.70072

El-Seedy, M.E., El-Hamdi, K.H., El-Harty, H.M.F. & Saeed, M.A. (2024): 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, http://doi.org/10.21608/ejss.2023.235525.1660

Fitzpatrick, R.W., Boucher, S.C., Naidu, R. & Fritsch (1994): Environmental Consequences of Soil Sodicity. *Australian Journal of Soil Resources,* 32: 1069-93, http://doi.org/10.1071/sr9941069

Gopal, B., Shetty, A., Jayaprakash & Chaya, D.Y. (2015): Spatial Variability of Topsoil Chemical Properties. *Indian Journal of Agricultural Research,* 49(2): 134-141, http://doi.org/10.5958/0976-058x.2015.00019.0

Ibrahim, J.A., Mbaya, A.L., Akande, D., Agaku, D.T. & Haruna, S. (2020): Impact of Toposequence on Soil Properties and Classification in Zaria, Kaduna State, Northern Guinea Savanna, Nigeria. *EQA – International Journal of Environmental Quality*, 38: 48–58, https://doi.org/10.6092/issn.2281-4485/10043

Ibrahim, M., Bello, A. & Yusuf, H. (2021): Soil Salinity and Crop Productivity in Irrigated Fields of Sokoto State, Nigeria. *Journal of Arid Environments,* 185: 104-338, https://doi.org/10.1016/j.jaridenv.2020.104338

Iwasaki, S., Endo, Y. & Hatano, R. (2017): The Effect of Organic Matter Application on Carbon Sequestration and Soil Fertility in Upland Fields of Different Types of Andosols. *Soil Science and Plant Nutrition,* 68(2): 200-220, http://doi.org/10.1080/00380768.2017.1309255

Jackson, M. L. (1958): Soil Chemical Analysis. *Agronomy Journal,* 50, 5, Englewood Cliffs, Prentice-Hall Inc., http://doi.org/10.2134/agronj1958.00021962005000050022x

James, G., Witten, D. Hastie, T. & Tibshirani, R. (2024): An Introduction to Statistical Learning: with Applications in R. *Springer Science & Business Media, 24,* ch. 5: Resampling Methods.

James, G., Witten, D., Hastie, T., & Tibshirani, R. (2023). An Introduction to Statistical Learning (2nd ed.). *Springer Texts in Statistics*. https://doi.org/10.1007/978-3-031-387470_5

James, L.A., Scott, C.J., Barnerd, L.A. Owen, M.J., Lang, M.S. & Jones, S.R. (2023): Sensitivity of Model Estimates of CME Propagation and Arrival Time to Inner Boundary Conditions. *Space Weather,* 21(4): http://doi.org/10.1029/2022sw003289

Kramer, I., Peleg, N & Mau, Y. (2025): Climate Change Shifts Risk of Soil Salinity and Degradation in Water-scarce Regions. *Agricultural Water Management,* 307: 109223, http://doi.org/10.1016/j.agwat.2024.109223

Lehmann, A., Zheng, W. & Rillig, M.C. (2017): Soil Biota Contributions to Soil Aggregation. *Nature Ecology & Evolution,* 1(12): 1828–1835, https://doi.org/10.1038/s41559-017-0344-y

Liu, Y., Zhu, L., Ding, L. & Sui, H. (2024): A Hybrid Sampling Method for Highly Imbalanced and Overlapped Data Classification with Complex Distribution. *Information Sciences,* 661, 4: 120117, https://doi.org/10.1016/j.ins.2024.120117

McLean, E.O. (1982): Soil pH and Lime Requirement. **In:** Methods of Soil Analysis, Part 2. (Edited by A.L. Page, R.H. Miller and D.R. Keeney). *American Society of Agronomy,* Madison, Wisc, 199-224, http://doi.org/10.2334/agronmonogr9.2.2ed.c12

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

Microsoft Corporation, *Microsoft Excel,* Version 16.0, Redmond, WA, USA: Microsoft, 2023.

Mohanavelu, A., Naganna, S.R. & Al-ansari, N. (2021): Irrigation Induced Salinity and Sodicity Hazards on Soil and Groundwater: An Overview of its Causes, Impacts and Mitigation Strategies. *Agriculture,* 11(10): 983, http://org/doi.10.3390/agriculture11100983

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

Narvaez-Ortiz, W.A., Reyes-Valdes, M.H., la Fuente, M.C. & Benavides-Mendoza, A. (2022): Multiple, Linear and Polynomial Models for Studying the dynamics of the Soil Solution. *Soil Systems,* 6, 2, (42), http://org/doi.10.3390/soilssystems6020042

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

Olaniyi, I.K., Adeosun, B.A. & Ojo, O.I. (2025): Climatic and Anthropogenic Influences on Soil Salinity and Groundwater Quality in Semi-Arid Irrigated Agriculture: A Review with Insights from Oba Dam, Nigeria. *Asian Journal of Research in Agriculture and Forestry*, 11(4): 179-187, https://doi.org//10.9734/ajraf/2025/v11i445

Ouzemou, J., Laamrani, A., El-Battay, A. & Whalen,J.K. (2025): Predicting Soil Salinity Based on Salt/Water Extracts in a Semi-Arid Region of Morocco. *Soil Systems,* 9(1): 3, http://doi.org/10.3390/soilssystems9010003

Pistocchi, C., Ragaglini, G., Colla, V., Branca, T.A., Tozzini, C. & Romaniella.L. (2017): Exchangeable Sodium Percentage Decrease in Saline-Sodic Soil after Basic Oxygen Furnace Slag application in a lysimeter trial," *Journal of Environmental Management*, 203(3): 896-906, http://doi.org/10.1016/j.jenvman.2017.05.007

Qadir, M., Schubert, S. & Prasad, N. (2025): Innovative Approaches for Sodicity Reduction in Semi-Arid Regions. *Land Degradation & Development*, 36(4): 1162-1178.

Qadir, A.A., Farooqi, Z.U.R., Ahmad, I., Sabir, M., Jamal, A., Hopkins, B.G. & Ashraf, M.N. (2025): Gypsum and Manure Impacts on Contrasting Textured Saline-Sodic Soils and Greenhouse Gas Emissions. *Journal of Soil Science and Plant Nutrition*. https://doi.org/10.1007/s42729-025-02852-8

Rodriguez-albarracin, H.S., Dematte, J.A.M., Rosin N.A., Contreras, A.E.D., Silvero, N.E.Q., Cerri, C.E.P., Mendes, W. & Tayebi, M. (2023): Potential of Soil Minerals to Sequester Soil Organic Carbon. *Geoderma*, 436, http://org/doi.10.1016/j.geoderma.2023.116549

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

Sappor, D.K., Osei, B.A. & Ahmed, M.R. (2017): Reclaiming Sodium Affected Soil: The Potential of Organic Amendments. *International Journal of Plant Science*, 16(2), http://doi.org/10.9734/ijpss/2017/33410

Shahabi, M., Jafarzadeh, A.A., Neyshabouri, M.R., Ghorbani, M.A. and Kamran, K.V. (2016): Spatial Modelling of Soil Salinity using Multiple Linear Regression, Ordinary Kriging and A Neutral Network Methods. *Archives of Agronomy and Soil Science* http://doi.10.1080/03650340.2016.1193162

Stavi, I., Thevs, N. & Priori, S. (2021): Soil Salinity and Sodicity in Drylands: A Review of Causes, Effects, Monitoring and Restoration Measures. *Frontiers in Environmental Science*, 9:712831, http://doi.org/10.3389/fenvs.2021.712831

Subhasree, N., Sajeen, S., Prasanthi, K. & Abdul Hakkim, V.M. (2022): Spatial Variability Mapping of Soil Chemical Properties using GIS and GPS. *International Journal of Environment & Climate Change*, 12(12): 512-520, http://doi.10.9734/ijecc/2022/v12i121488 Sumner, M.E. (1993): Sodic Soils – New Perspectives. *Soil Research*, 31(6): 683–750, https://doi.org/10.1071/SR9930683

Tuncay, T., Kilic, S., Dedeoglu, M. Dengiz, O., Baskan, O. & Bayramin, I. (2021): Assessing Soil Fertility Index Based on Remote Sensing and GIS Techniques with Field Validation in Semi-Arid Agricultural Ecosystem. *Journal of Arid Environments*, 190: 104525, http://doi.org/10.1016/j.jaridenv.2021.104525

Tuncay, T., Bayramin, I., Atalay, F. & Unver, I. (2016): Assessment of Inverse Distance Weighted (IDW) Interpolation on Spatial Variability of Selected Soil Properties in the Cukurova Plain, *Journal of Agricultural Sciences*, 22(3): 377-384, http://doi.org/10.1501/tarimbil_0000001396

Walkley, A.J. & Black, I.A. (1934): Estimation of Organic Carbon by the Chromic Acid Titration Method. *Soil Science*, 37: 29-38, http://doi.org/10.1097/00010694183401000-00003

Wang, S., Yao, X., Zhang, Z., He, X. & Ye, S. (2020): Soil Aggregation and Aggregate-Related Exchangeable Base Cations under Different Aged Tea Plantations in Southern Guangxi, China. *Soil Science and Plant Nutrition*, 66(4): 636–644, https://doi.org/10.1080/00380768.2020.1780471

Wang, H., Ren, T., Feng, Y., Liu, K., Feng, H., Liu, G. & Shi, H. (2020): Effects of the Application of Biochar in Four Typical Agricultural Soils in China. *Agronomy*, 10(11): 1649, http://doi.org/10.3390/agronomy1000111649

Wang, K., Li, J., Zhou, Z. & Zhang (2023): Editorial: Soil Degradation and Restoration in Arid and Semi-Arid Regions. *Frontiers in Environmental Science*, 11:1307500, http://doi.org/10.3389/fenvs.2023.1307500

Wang, Y., Gao, M., Chen, H., Fu, X., Wang, L., & Wang, R. (2023): Soil Moisture and Salinity Dynamics of Drip Irrigation in Saline-Alkali Soil of Yellow River basin. *Frontiers in Environmental Science*, 11: 1130455, https://doi.org/10.3389/fenvs.2023.1130455

Wang, Y., Yin, Y., Joseph, S., Flury, M. Wang, X., Tahery, S., Li, B. & Shang, J. (2023): Stabilization of Organic Carbon in Top and Sub-Soil by biochar Application into Calcareous Farmlands. *Science of the Total Environment*, 907, http://org/10.1016/j.scitotenv.2023.168046

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