

Article

Prediction of Soil Salinity Parameters in the Songnen Plain Using FOD Processing and Machine Learning from Measured Hyperspectral Reflectance Under Different Surface Conditions

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Highlights

What are the main findings?

- Surface conditions affect the spectral response of soil salinity parameters, with cracked surface conditions being superior to uncracked surface conditions.
- Compared with the original spectral reflectance, the correlation between the FOD spectral indices and salt parameters (EC and pH) has been significantly improved.

What are the implications of the main findings?

- This study confirmed the application potential of the hyperspectral fractional differential processing method in the inversion of soil salinity parameters.
- This method enables regional-scale hyperspectral monitoring of soil salinity, supporting faster remediation of local salinization.

Abstract

Soil salinization severely restricts ecosystem stability and the sustainable development of agricultural productivity. However, current understanding of the spectral–salinity quantitative relationships under the influence of surface cracking still remains limited. To address this gap, this study collected hyperspectral reflectance data (350–2500 nm) from salt-affected soil in both cracked and uncracked surface conditions across the Songnen Plain, and applied fractional-order differentiation (FOD) processing with orders ranging from 0 to 2 and a step size of 0.1. Based on this, 14 types of FOD spectral indices were constructed, incorporating one-dimensional (1D), two-dimensional (2D), and three-dimensional (3D) structures. For each spectral index, the optimal fractional order and corresponding band combinations were first selected through Pearson correlation analysis for pH and EC under both surface conditions; subsequently, feature selection was performed using XGBoost-SHAP explainable analysis among the 14 optimal indices across different dimensions. Furthermore, the predictive performance of four modeling methods, including partial least squares regression (PLSR), Gaussian process regression (GPR), support vector regression (SVR), and random forest regression (RFR), was evaluated. The results showed that FOD transformations significantly enhanced correlations with EC and pH compared to raw reflectance. All prediction models demonstrated higher prediction accuracy under cracked surface conditions than uncracked surface conditions, indicating that desiccation cracks positively modulate spectral signals to enhance salinity information expression. Across different surface states, model performance generally followed the ranking: PLSR > GPR > SVR > RFR,



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with PLSR achieving the best predictions for EC and pH under cracked surfaces (R^2 of 0.88 and 0.76, RMSE of 0.29 dS/m and 0.35). This study not only deepens the understanding of fractional-order spectral response mechanisms in saline–alkali soils but also provides methodological support for regional monitoring of soil salinization.

Keywords: soil salinization; Songnen Plain; spectral differentiation; feature selection; desiccation crack

1. Introduction

The soil environment situation in China is becoming increasingly severe with its rapid industrialization, urbanization, intensification of agriculture and global changes [1]. As one of the most prevalent soil degradation forms, soil salinization compromises soil structural integrity, diminishes fertility, reduces agricultural productivity, and ultimately lowers crop yields [2–4]. The total area of saline–alkali soil in China is 3.69×10^7 ha, exhibiting significant potential for reclamation and sustainable utilization. Comprehensive remediation and rational utilization of saline–alkali lands can drive the expansion, quality enhancement, and efficiency improvement of arable land systems. Such efforts hold substantial practical and strategic importance for advancing agricultural sustainability and supporting the development of a modern, ecologically sound countryside. Therefore, accurate estimation of soil salinity information is not only a foundational requirement for effective salinization mitigation but also a globally recognized scientific priority and frontier research domain, which further provides crucial support for accurately identifying the coupled natural and human drivers underlying the spatiotemporal evolution of soil salinization [5].

Systematic clarification and dynamic updating of fundamental information including the spatial extent, geographic distribution, typological classification, and salinization severity of saline–alkali land in China still remain urgent [6]. Conventional soil salinity monitoring relies predominantly on field sampling coupled with laboratory-based chemical analysis. However, this approach exhibits inherent limitations in accuracy due to constraints on sample representativeness, sampling point density, and spatial coverage uniformity. Furthermore, measurement outcomes are susceptible to interference from topographic variability, surface cover conditions, and localized microclimatic factors, collectively undermining the regional scalability and generalizability of monitoring results [7–10]. While electromagnetic induction enables rapid, non-contact estimation of soil apparent electrical conductivity [11], its operational reliability is highly dependent on precise instrument calibration, strict adherence to standardized protocols, and stable environmental conditions [12–14]. In contrast, remote sensing technology is characterized by its synoptic perspective, temporal repeatability, cost efficiency, and broad spatial coverage, which has emerged as a cornerstone methodology for large-scale, dynamic monitoring of soil salinization at both regional and global levels [15–17]. Hyperspectral remote sensing, in particular, offers nanometer-scale spectral resolution, markedly improving the capacity to detect the subtle spectral signatures associated with saline–alkali soils. This capability proves especially valuable for discriminating among salt mineral species, identifying diagnostic absorption features, and quantitatively retrieving salt content, thereby conferring distinct methodological advantages [18,19]. Moreover, hyperspectral data underpin essential preprocessing and inversion steps, including radiometric calibration, ground truth validation, spectral unmixing of heterogeneous pixels, and supervised classification modeling of saline–alkali land [20,21]. Likewise, prevailing remote sensing-based approaches for saline–alkali land mapping fundamentally rely on comparative spectral analysis: distin-

guishing saline–alkali soils from other land surface types through systematic examination of their unique spectral behavior [22,23]. Critically, the spectral response of saline–alkali soils arises from resonance interactions among dissolved salt ions; the identity, concentration, and aggregate abundance of these ions exert a direct influence on diagnostic spectral features [24–26]. Accordingly, rigorous quantification of the relationships linking soil salt composition, total salt content, and the corresponding spectral responses constitutes not only a scientific prerequisite for enhancing inversion accuracy but also a strategic enabler for transitioning soil salinization monitoring from qualitative delineation to operationally viable, high-frequency, large-area quantitative assessment.

Currently, the development of inversion models for soil salinity estimation has emerged as a prominent research focus. Numerous studies have established empirical or semi-empirical models by coupling field-measured diagnostic spectral reflectance data with in situ soil electrical conductivity (EC) or salt concentration measurements, thereby enabling quantitative prediction of soil salinity [27]. Other researchers have leveraged spectral-derived indices extracted from hyperspectral imagery to map soil salinity and its spatial heterogeneity [28]. In regions with similar soil properties, spectral indices established based on soil salt content and spectral bands can be used to construct models for effective prediction of soil salt content within the study area [29–31]. Furthermore, recent methodological advances explore the utility of mathematical preprocessing techniques applied to reflectance spectra to enhance model sensitivity and generalizability [32,33]. Among them, fractional-order differentiation (FOD) is a mathematical transformation method specifically designed for spectral data. Compared to traditional integer-order differentiation, FOD introduces a continuously adjustable derivative order within the range of 0–2, enabling enhanced gradient amplification of subtle spectral features and thus more accurately and adaptively extracting latent spectral responses closely related to soil information [34,35]. However, practical applications of FOD in remote sensing-based soil salinity inversion remain limited, with insufficient multi-scale, systematic validation across diverse zones. The universality and robustness of the associated methods still require further evaluation. Fractional differentiation, in particular, offers a more nuanced and adaptive means of amplifying subtle, salt-related spectral features compared with conventional integer-order differentiation, owing to its ability to tune differentiation order continuously between zero and two. Nevertheless, applications of fractional calculus in soil salinity inversion remain scarce, indicating that systematic validation across diverse agro-ecological settings is still lacking.

Soil salinity estimation using spectroscopy is critically dependent on the selection of robust and representative spectral features. However, the substantial variability in soil composition, physicochemical properties, parent material, measurement protocols, and surface conditions leads to considerable heterogeneity among the candidate characteristic variables, thereby complicating model development and generalizability. To address this challenge, rigorous feature selection is essential, which enables dimension reduction, enhances model interpretability, mitigates overfitting, improves predictive accuracy, reduces computational burden, and shortens inference time. Widely adopted feature selection techniques include variable importance projection (VIP), principal component analysis (PCA), competitive adaptive reweighted sampling (CARS), genetic algorithm (GA), and Pearson correlation analysis [36–39]. Despite their methodological maturity and computational efficiency, these approaches often incorporate stochastic components, resulting in inconsistent feature subsets across repeated runs and suboptimal stability in feature learning, ultimately compromising the reliability and reproducibility of soil parameter predictions. Accurate modeling of soil salt content remains a central objective in hyperspectral salinity assessment. Unlike empirically derived spectral indices, multivariate predictive models are

not constrained by fixed dimensional assumptions and can more comprehensively capture nonlinear relationships between spectral signatures and soil salinization processes, making them indispensable for quantitative, mechanistic interpretation.

The Songnen Plain constitutes one of China's most extensive and severely affected regions of saline-alkali soil, and serves as a key strategic area for the integrated development and sustainable utilization of such degraded land. Owing to its predominantly clayey soil texture, saline-alkali soils in this region exhibits pronounced desiccation-induced shrinkage and cracking upon evaporation. However, current studies rarely account for the surface physical state in spectral analysis, limiting mechanistic understanding of cracked saline-alkali soils [40]. To bridge this gap, spectral reflectance data under natural field drying conditions for both fully cracked and partially uncracked surface states were used. After applying fractional-order differentiation transforms to the raw reflectance across orders from 0.1 to 2.0 with a step of 0.1, 14 types of spectral indices were extracted for each fractional order, capturing one-dimensional, two-dimensional, and three-dimensional structural features. By systematically analyzing the trends in Pearson correlation coefficients between these spectral indices and soil EC and pH at different fractional orders, the optimal differentiation order was determined for each spectral index that maximizes the sensitivity to salinity indicators. Subsequently, the XGBoost-SHAP method was carried out to select the most effective combinations of spectral indices for predicting EC and pH. Based on this, four predictive models such as partial least squares regression (PLSR), Gaussian process regression (GPR), support vector regression (SVR), and random forest regression (RFR) were constructed and compared to evaluate their performance. This study establishes a hyperspectral monitoring framework for surface soil salinity that integrates physical mechanisms and focuses on surface conditions, aiming to achieve precise and efficient monitoring of soil salinity at the regional scale, thereby accelerating local efforts to improve soil salinization. The full workflow is shown in Figure 1.

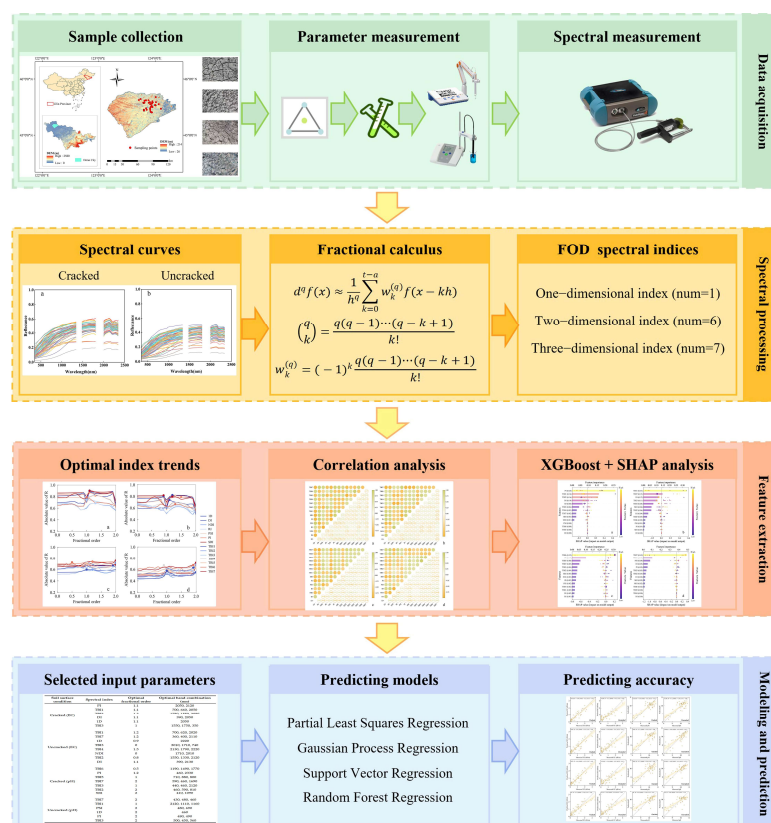


Figure 1. Technical flowchart.

2. Materials and Methods

2.1. Study Area

This study was conducted in Da'an City, situated within the western Songnen Plain, which is commonly considered as one of the world's three principal regions characterized by soda salt-affected saline soils. Da'an City exhibits a typical temperate continental monsoon climate, characterized by an annual mean evaporation substantially exceeding annual precipitation. This imbalance in the water–heat regime, combined with regional hydrological conditions and geological structures, constitutes a key natural driver of soil salinization. Moreover, the relatively high clay content in local soils promotes frequent desiccation and cracking during evaporation (shown in Figure 2b–e), thereby enhancing the spatial heterogeneity of surface soil salinity. To account for the dynamic nature of surface cracking, the inherent spatial variability of salinity, and the multifaceted influence of environmental factors, in situ spectral measurements across 57 distinct surface cracking configurations were conducted during the dry season (Figure 2a). Concurrently, all soil samples were collected from the three vertices of a 1 m side triangle at a depth of 0–20 cm for each sampling site, mixed thoroughly, and then oven-dried at 105 °C for 24 h in the laboratory. Subsequently, all soil samples were ground and passed through a 2 mm sieve for the measurement of soil salinity parameters. Specifically, a soil suspension with a water-to-soil mass ratio of 5:1 was prepared. After that, the pH and EC were determined by the potentiometry method and conductometry method, respectively.

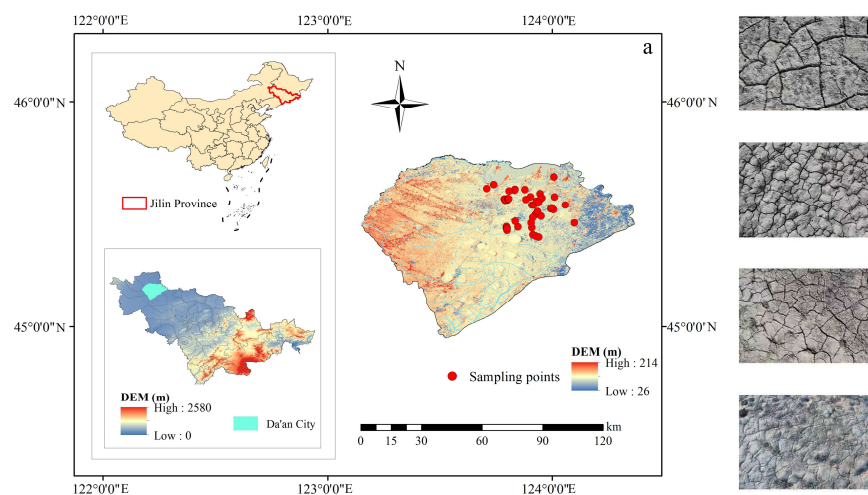


Figure 2. Study area. (a) Distribution of sampling sites, and (b–e) cracked surfaces of saline–alkali soils observed in the Songnen Plain.

2.2. Measurement and Preprocessing of Spectral Reflectance

In this study, spectral reflectance measurements were conducted using an ASD Field-Spec 3 spectrometer (Analytical Spectral Devices, Boulder, CO, USA) across the wavelength range of 350–2500 nm. Note that all sampling sites strictly followed a standardized in situ spectral measurement procedure under natural field conditions. Specifically, prior to collecting each soil sample, a fiber-optic probe with a 25° field of view was used to acquire reflectance spectra from both the cracked and adjacent uncracked areas at a vertical height of 1.0 m above ground, covering a circular observation area on the soil surface with a diameter of 44.34 cm. Before each spectral measurement, the instrument underwent dark current correction, followed by radiometric calibration using a certified white reference panel. Afterward, ten sets of spectral data were consecutively collected for each sampling site and surface condition, and their arithmetic mean spectrum was calculated as the representative reflectance spectrum. Subsequent spectral preprocessing included

the removal of outlier data points (breakpoint correction), smoothing using a nine-point moving average filter, and resampling across the entire wavelength range to a uniform spectral resolution of 10 nm. Furthermore, to eliminate the interference from residual soil moisture on spectral responses, three strong water-absorption bands (1350–1480 nm, 1800–2000 nm, and 2350–2500 nm) within the near-infrared and shortwave infrared bands were systematically excluded, thereby generating the final spectral reflectance data used in subsequent analyses.

2.3. Extraction of Fractional-Order Spectral Indices

Although traditional integer-order differential algorithms can reduce the noise impact of hyperspectral satellite data, enhance the detailed features of spectral data, and separate overlapping peaks of spectral curves, their description of spectral information is discrete and discontinuous. The influence of soil salinity changes on spectra is complex and continuous, indicating that integer-order differentiation may not fully capture spectral information. Fractional-order differentiation is an extension of integer-order differentiation, with its order being any real number between 0 and 2. It can describe the continuous spectral change behavior between integer orders and detect subtle, continuous spectral variation features, thereby improving the inversion accuracy of spectral modeling results. Its essence lies in FOD effectively suppressing environmental and instrumental noise through continuously adjustable fractional orders, while enhancing weak signals in soil spectra, thereby improving the spectral response intensity of soil information [41]. In this study, the Grünwald–Letnikov definition method is used to calculate the spectral differentiation of soil samples under both cracked and uncracked surface conditions [42–44]. The formula is as follows:

$$d^q f(x) \approx \frac{1}{h^q} \sum_{k=0}^{t-a} w_k^{(q)} f(x - kh), \quad (1)$$

where q represents the differential order, h refers to the sampling interval, t and a are the upper and lower limits of the differential; k is the summation index; and the weight coefficient is $w_k^{(q)} = (-1)^k \binom{q}{k}$, where the binomial coefficient $\binom{q}{k}$ can be calculated through the Gamma function [45]:

$$\binom{q}{k} = \frac{q(q-1) \cdots (q-k+1)}{k!}, \quad (2)$$

The formula for the weight coefficient can be further expressed as:

$$w_k^{(q)} = (-1)^k \frac{q(q-1) \cdots (q-k+1)}{k!}, \quad (3)$$

In this study, the sampling interval h is set at 10 nm, the upper limit of differentiation t is set at 2, the lower limit of differentiation a is set at 0, and the fractional step size is 0.1. To further enhance the effective information of the spectrum, and provide a data basis for the high-spectrum inversion modeling of soil salinity, the results of spectral differentiation in this study are refined into different dimensions. After that, one-dimensional, two-dimensional, and three-dimensional spectral indices are respectively constructed. Among them, the one-dimensional spectral index is the result of the differentiation processing of the spectral reflectance of each band; the two-dimensional spectral indices are the combination calculation of the spectral differentiation data of any two bands, with the calculation formulas shown in Table 1 [46–48]; and the three-dimensional spectral indices are the combination calculation of the spectral differentiation data of any three bands, with the calculation formulas shown in Table 2 [17].

Table 1. 2D spectral indices.

Spectral Index	Formula
Difference Index (DI)	$R_{\lambda 1} - R_{\lambda 2}$
Normalized Difference Index (NDI)	$\frac{R_{\lambda 1} - R_{\lambda 2}}{R_{\lambda 1} + R_{\lambda 2}}$
Ratio Index (RI)	$\frac{R_{\lambda 1}}{R_{\lambda 2}}$
Perpendicular Spectral Index (PSI)	$\frac{R_{\lambda 1} + M \times R_{\lambda 2}}{\sqrt{M^2 + 1}}$
Product Index (PI)	$R_{\lambda 1} \times R_{\lambda 2}$
Spectral Radial Index (SRI)	$\sqrt{R_{\lambda 1}^2 + R_{\lambda 2}^2}$

$R_{\lambda 1}, R_{\lambda 2}$: The spectral differential data of any two bands, $\lambda 1 \neq \lambda 2$; $M = 1.0563$: slope of the soil line extracted using reflectance in the bands of 655 nm and 865 nm [49,50].

Table 2. 3D spectral indices.

Spectral Index	Formula
Three-Band Index 1 (TBI1)	$\frac{R_{\lambda 1}}{R_{\lambda 2} \times R_{\lambda 3}}$
Three-Band Index 2 (TBI2)	$\frac{R_{\lambda 1}}{R_{\lambda 2} + R_{\lambda 3}}$
Three-Band Index 3 (TBI3)	$\frac{R_{\lambda 1} - R_{\lambda 2}}{R_{\lambda 1} + R_{\lambda 3}}$
Three-Band Index 4 (TBI4)	$\frac{R_{\lambda 1} - R_{\lambda 2}}{R_{\lambda 1} - R_{\lambda 3}}$
Three-Band Index 5 (TBI5)	$\frac{R_{\lambda 1} + R_{\lambda 3}}{R_{\lambda 1} + R_{\lambda 2}}$
Three-Band Index 6 (TBI6)	$\frac{R_{\lambda 3} - R_{\lambda 2}}{(R_{\lambda 1} - R_{\lambda 2}) - (R_{\lambda 1} - R_{\lambda 3})}$
Three-Band Index 7 (TBI7)	$(R_{\lambda 1} - R_{\lambda 2}) - (R_{\lambda 1} - R_{\lambda 3})$

$R_{\lambda 1}, R_{\lambda 2}, R_{\lambda 3}$: The spectral differential data of any three bands, $\lambda 1 \neq \lambda 2 \neq \lambda 3$.

2.4. Correlation Analysis

To achieve the optimal selection of fractional orders of spectral indices under different dimensions, this study conducted correlation analysis and calculated the absolute values of correlation coefficients for all band combinations and each fractional order. After that, the optimal fractional order spectral index sets under different dimensions were extracted under various surface conditions. The formula for calculating the correlation coefficient is as follows:

$$r = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^n (x_i - \bar{x})^2} \sqrt{\sum_{i=1}^n (y_i - \bar{y})^2}}, \quad (4)$$

where n represents the number of soil samples, x_i indicates the measured EC and pH of the i -th sample, and y_i is the extracted fractional spectral index of the corresponding sample. $\bar{x}$ and $\bar{y}$ respectively denote the average values of the salt content and fractional spectral index.

2.5. Spectral Feature Selection

Although spectral indices contain a lot of spectral information, there are very obvious problems of data redundancy and overlap. Screening multi-dimensional spectral indices under different fractional orders not only reduces the data dimension but also avoids overfitting of prediction models. For the optimal fractional order spectral index sets under different dimensions, this study uses XGBoost combined with SHAP analysis to further screen the spectral feature parameters. Specifically, SHAP analysis is a model-agnostic interpretability framework grounded in cooperative game theory. It rigorously attributes the output of a predictive model to individual input features by computing Shapley values,

thereby enabling principled feature importance assessment and informed feature selection. The SHAP value can be calculated using the formula as follows [51]:

$$\phi_i = \sum_{S \subseteq F \setminus \{i\}} \frac{|S|!(|F| - |S| - 1)!}{|F|!} [f_{S \cup \{i\}}(x_{S \cup \{i\}}) - f_S(x_S)], \quad (5)$$

where ϕ_i denotes the SHAP value of feature i ; F represents the set of all features; and S denotes a subset of features excluding feature i . $|S|$ and $|F|$ indicate the number of features in the subset and the full set, respectively. $f_S(x_S)$ represents the expected model output conditioned on the feature subset S . In this study, an XGBoost model was first constructed, and the SHAP values for each feature were computed. The mean absolute SHAP value across all samples was used as the metric of feature importance. This study employed the Boruta algorithm to construct shadow features for feature importance evaluation with the importance threshold set at 0.3, which was determined through multiple iterations based on the statistical significance of the distribution between the original and corresponding shadow features, ensuring that the selection results are supported by robust statistical criteria [52,53].

2.6. Prediction Models

Based on the selected FOD spectral indices in Section 2.5, EC and pH prediction models applicable to different surface conditions were further developed, incorporating four machine learning methods: partial least squares regression (PLSR), Gaussian process regression (GPR), support vector regression (SVR), and random forest regression (RFR). Specifically, PLSR is a supervised modeling method that combines principal component analysis with multiple linear regression; it simultaneously decomposes both independent variables (spectral indices) and dependent variables (EC/pH), extracting latent variables that maximize covariance to establish a regression relationship. Note that although PLSR originates from the statistical framework, it has also been widely incorporated into machine learning methods due to its data-driven nature, feature integration capability, and generalization modeling power. GPR, on the other hand, is a fully Bayesian, non-parametric probabilistic regression method that models unknown functions through prior covariance functions, offering both accuracy and robustness even under high-dimensional, small-sample scenarios [54]. SVR maps samples into a high-dimensional feature space via kernel functions and derives an optimal regression hyperplane under ϵ -insensitive loss constraints, thereby robustly capturing the response relationship between the spectra and salinity parameters [55]. RFR operates within a Bagging ensemble framework, introducing random subsampling of feature subsets during decision tree training, effectively reducing variance, mitigating overfitting, and significantly enhancing model generalization performance under limited sample conditions [56]. Given the limited sample size in this study, soil samples were first sorted according to the measured EC and pH values to achieve balanced coverage across gradients of both salinity parameters. Subsequently, all four models were uniformly evaluated using a nested cross-validation strategy consisting of outer 3-fold and inner 3-fold validation: the outer loop provided unbiased assessment of each model's generalization performance, while the inner loop was dedicated to hyperparameter grid search and model fitting. This design strictly adheres to independence principles throughout data partitioning, model training, and performance evaluation, systematically avoiding model selection bias and overestimation of performance, thus providing a methodological foundation for the scientific validity, credibility, and reproducibility of the EC and pH prediction results.

3. Results

3.1. Measurements of Salt Parameters

The analysis statistics of salt information are shown in Table 3. It can be seen that the EC values ranged from 0.06 to 3.39 dS/m, with an average of 0.97 dS/m. Additionally, the standard deviation (SD) of the EC is 0.84 dS/m, and the coefficient of variation (CV) is 86.64%, indicating that the EC varies significantly and can thus well reflect the salinity status of the soil in Songnen Plain. The table also indicates that the pH values of the soil samples covered a range from 8.01 to 10.77, with an average of 9.83, a standard deviation of 0.73, and a coefficient of variation of 7.41%, suggesting that the soil samples generally shows a stable strong alkaline characteristic. Therefore, the soil samples in this study refer to typical saline–alkali soil, according to the discrimination criteria proposed by Zhang et al. [57].

Table 3. Statistical description of the salinity parameters of the soil samples.

Soil Parameter	Min	Max	Mean	SD	CV(%)	Skewness	Kurtosis
EC (dS/m)	0.06	3.39	0.97	0.84	86.64	1.02	0.56
pH	8.01	10.77	9.83	0.73	7.41	−1.14	0.18

n = 57; SD: Standard deviation; CV: coefficient of variation.

3.2. Spectral Processing Results

Figure 3 shows the original reflectance spectral curves of all soil samples under two surface conditions. It can be seen that across the full wavelength range of 500–2500 nm, all samples exhibit a monotonic increase in reflectance with increasing wavelength: reflectance in the short-wave visible region (around 500 nm) ranges from 0.05 to 0.15, rising to 0.40–0.65 in the near-infrared to short-wave infrared region (around 2500 nm). Differences among samples are primarily reflected as systematic shifts in overall reflectance levels rather than significant changes in spectral shape. Specifically, in the short-wave region (500–1000 nm), reflectance variation is relatively small, indicating low sensitivity of this band to surface physical conditions; however, in the long-wave region, reflectance dispersion increases noticeably. Notably, although the spectral shapes of cracked and uncracked surfaces are highly consistent, the former exhibits significantly lower overall reflectance than the latter.

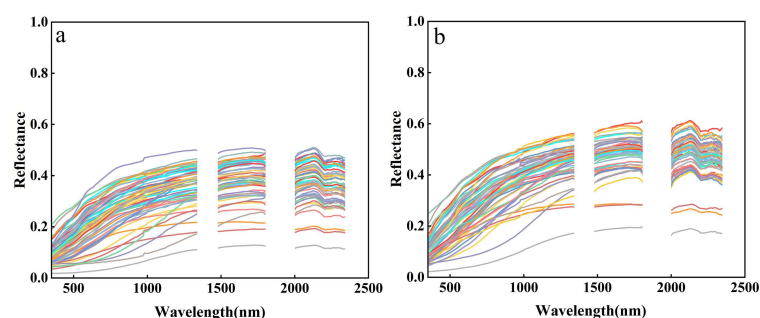


Figure 3. Original spectral reflectance curves under different surface conditions: (a) cracked soil samples; and (b) uncracked soil samples.

Figures 4 and 5 show the spectral reflectance differentiation results of all soil samples under cracked and uncracked surface conditions, respectively, for different fractional derivative orders. The red lines represent the mean fractional derivative spectra at each order, while the blue shaded areas indicate the corresponding standard deviations. Overall, as the derivative order increases, the spectral curves exhibit systematic evolution: the absorption feature peaks gradually narrow, their intensities weaken, and the overall deriva-

tive values tend toward zero. This indicates that fractional-order differentiation effectively suppresses spectral baseline drift and enhances the distinguishability of overlapping absorption features [58]. Further comparison between the two surface conditions reveals that fractional-order differentiation maintains invariance in the general transformation patterns of the spectra regardless of surface morphology. However, within the low-order derivative range (0–0.8), the standard deviation range for cracked surfaces is slightly larger than that for uncracked surfaces, reflecting relatively higher spatial heterogeneity in their spectral responses. In contrast, within the high-order derivative range (1.0–2.0), both the mean and dispersion of the differential spectra converge, leading to a significant reduction in spectral feature differences between the two surface types.

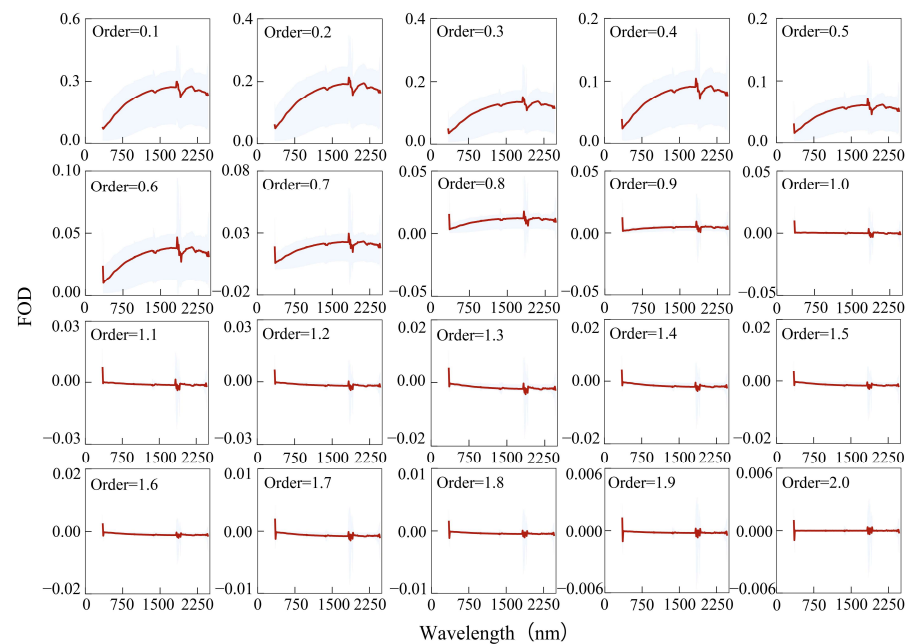


Figure 4. FOD spectral curves under the cracked surface condition.

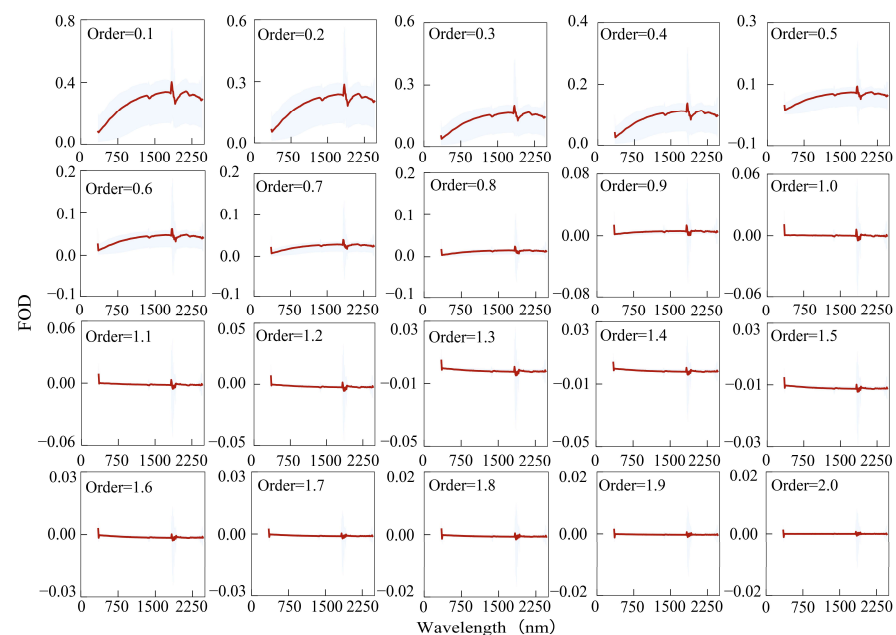


Figure 5. FOD spectral curves under the uncracked surface condition.

3.3. Results of Correlation Analysis

Figure 6 illustrates the variation of the maximum correlation coefficients between 14 differential spectral indices and salinity parameters as a function of the differentiation order. The results show that, under both surface conditions, all spectral indices exhibit significant surface dependency in their correlations with EC and pH: the maximum correlation coefficients obtained under cracked surfaces are generally higher than those under uncracked surfaces, indicating that surface crack structures enhance the sensitivity of spectral differentiation features to salinity parameters. The peak positions of the curves correspond to the optimal differentiation orders and the maximum achievable correlation coefficients for each index. Specifically, under cracked surfaces, the maximum correlation coefficients between the FOD spectral indices and EC are highly concentrated at differentiation orders of 1.0, 1.1, and 1.3, whereas under uncracked surfaces, the differentiation orders associated with the highest correlation coefficients for 14 indices and EC are relatively scattered, though most still fall within the fractional-order range of 0.9–1.2, highlighting the central role of first-order differentiation. Furthermore, under both surface conditions, the maximum correlation coefficients between each FOD spectral index and pH are significantly clustered around integer orders one and two, reflecting a stronger structural preference of pH-related spectral responses toward integer-order differentiation.

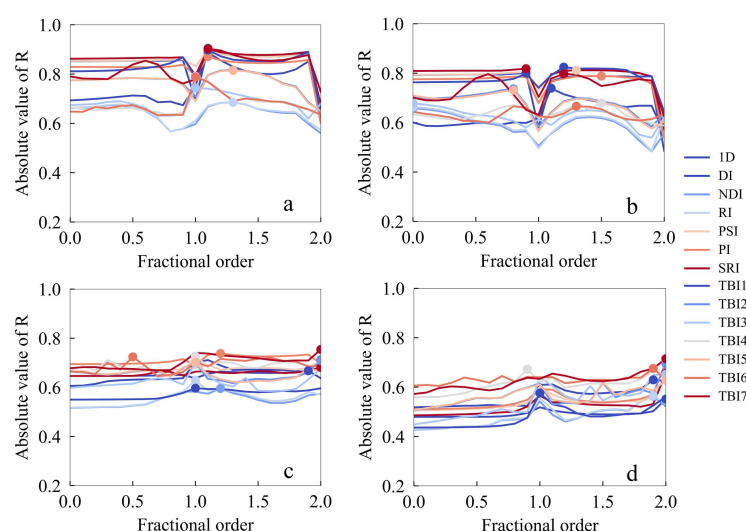


Figure 6. Variation curves of the maximum correlation coefficients between FOD spectral indices and salinity parameters with differential orders. (a) EC-cracked; (b) EC-uncracked; (c) pH-cracked; (d) pH-uncracked.

To systematically evaluate the strength and stability of the relationship between the optimal FOD spectral indices and soil salinity parameters, this study generated correlation coefficient heatmaps, shown in Figure 7. The results indicate that significant positive correlations are widespread among different indices, with prominent multicollinearity and high spectral information redundancy. Moreover, the average correlation coefficients among indices under cracked surface conditions were significantly higher than those under uncracked surfaces, suggesting that surface cracks further intensify the homogenized spectral response. Additionally, the spatial distribution patterns of the heatmaps corresponding to EC and pH were highly consistent under the same surface condition, indicating that the correlations among indices mainly stem from their intrinsic spectral construction mechanisms rather than differences in the physicochemical properties, which further underscores the necessity of conducting feature selection prior to developing inversion models.

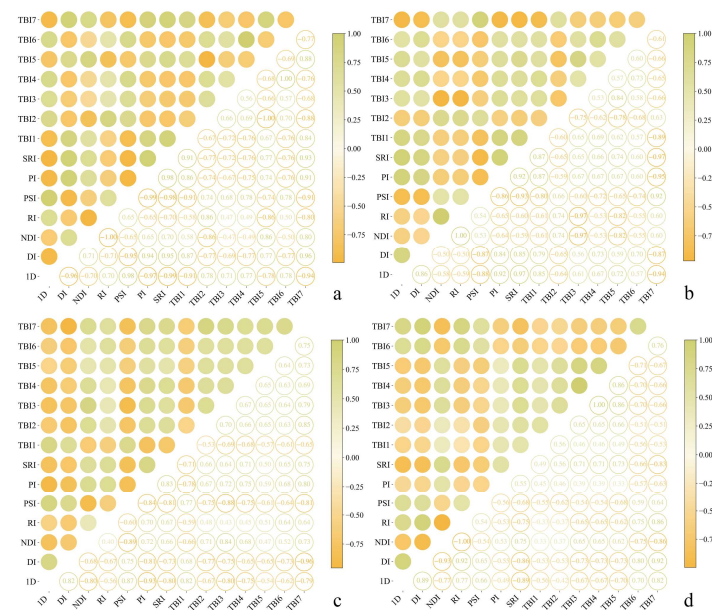


Figure 7. Heatmaps of correlation coefficients between FOD indices and salinity parameters. (a) EC-cracked; (b) EC-uncracked; (c) pH-cracked; (d) pH-uncracked.

3.4. Screening Results of Spectral Features

The screening results of the optimal FOD spectral indices under different surface conditions are shown in Figure 8. From the figure, it is evident that for the same soil parameter, the ranking of the feature importance, relative contribution, and influence direction of corresponding spectral indices differs significantly between different surface conditions. Regarding EC, TBI1, 1D, TBI3, TBI2, and DI maintain high feature importance under both surface conditions, demonstrating strong robustness. In contrast, TBI7, PI, and TBI3 exhibit superior and more stable applicability for pH. Furthermore, 3D spectral indices generally show higher overall feature contributions than 1D and 2D spectral indices, indicating their stronger spectral response sensitivity and information representation capability for soil salinity parameters, particularly for those related to alkaline salts, which is highly consistent with previous findings by Wang et al. and Zhang et al. [59,60].

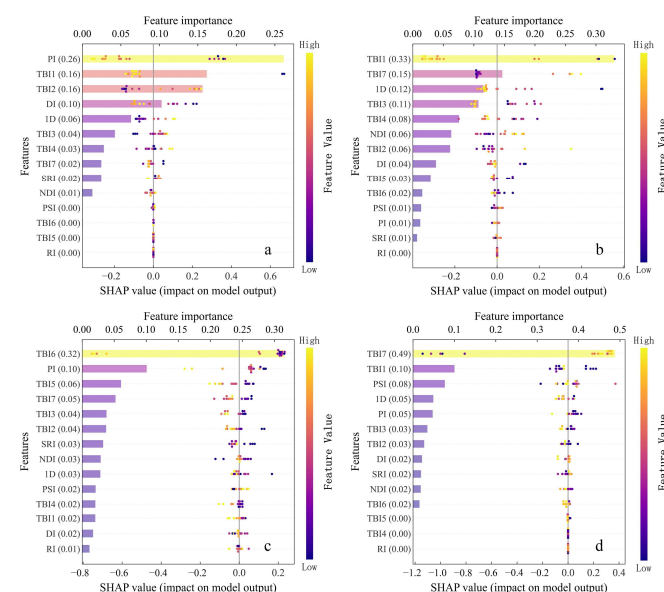


Figure 8. Ranked feature importance. (a) EC-cracked; (b) EC-uncracked; (c) pH-cracked; (d) pH-uncracked.

Table 4 presents the feature selection results and specific band combinations of the optimal FOD spectral indices under different surface conditions. It can be observed from the table that, after excluding strong water vapor absorption bands in the spectral ranges of 1350–1450 nm, 1800–1950 nm, and 2450–2550 nm, the selected band combinations for the FOD spectral indices generally fall within the typical spectral response regions of sodium carbonate and sodium bicarbonate, approximately ranging from 2000 to 2300 nm [61–63]. This distribution pattern is highly consistent with data from the USGS mineral spectral library, JPL Spectral Library, and multiple laboratory-controlled sample measurements, providing strong evidence at the mineral spectral response mechanism level that the selected FOD spectral indices possess clear physical significance, high interpretability, and robust modeling performance in soil salinity inversion, particularly in identifying alkaline salt components.

Table 4. Screened FOD spectral indices and corresponding band combinations.

Soil Surface Condition	Spectral Index	Fractional Order	Band Combination (nm)
Cracked (EC)	PI	1.1	2050, 2120
	TBI1	1.1	700, 660, 2050
	TBI2	1.3	1750, 1550, 2050
	DI	1.1	390, 2050
	1D	1.1	2050
	TBI3	1	1550, 1750, 350
Uncracked (EC)	TBI1	1.2	700, 620, 2020
	TBI7	1.2	360, 400, 2110
	1D	0.9	2220
	TBI3	0	2010, 1710, 740
	TBI4	1.5	2130, 1790, 2220
	NDI	0	1710, 2010
	TBI2	0.8	1550, 1330, 2120
	DI	1.1	390, 2130
Cracked (pH)	TBI6	0.5	1190, 1490, 1770
	PI	1.2	460, 2330
	TBI5	1	710, 880, 800
	TBI7	2	590, 460, 1690
	TBI3	1	440, 460, 2120
	TBI2	2	460, 590, 810
	SRI	2	410, 1090
Uncracked (pH)	TBI7	2	430, 480, 460
	TBI1	1	2120, 1110, 1160
	PSI	2	480, 690
	1D	2	460
	PI	2	480, 490
	TBI3	2	500, 450, 560

3.5. Predicted Results of Soil Parameters

To systematically evaluate the overall fitting capability and prediction robustness of the four prediction models developed in this study, scatter plots of the predicted values versus measured values for EC and pH were generated at the full sample scale under two surface conditions, as shown in Figure 9. These evaluations were conducted on the outer data of the nested cross-validation strategy, with key accuracy metrics such as the R^2 , RMSE, and LCCC calculated. From the figure, it is evident that across different surface conditions, all models demonstrated significantly higher prediction accuracy for EC than for pH, indicating that EC exhibits stronger and more stable spectral response signals. Figure 9 also

reveals that, under identical modeling approaches, prediction performance was generally superior under cracked surface conditions compared to uncracked conditions, indicating a trend consistent with earlier findings from spectral–salinity correlation analysis, which further supported the hypothesis that surface cracking enhances salinity-related spectral signals. Additionally, the PLSR model performed best in predicting both EC and pH, particularly excelling in predicting EC under cracked surface conditions ($R^2 = 0.88$, RMSE = 0.29 dS/m, LCCC = 0.94). GPR showed slightly better performance than SVR, and both models achieved moderate accuracy levels. In contrast, RFR exhibited the weakest overall performance; even under cracked surface conditions, its R^2 , RMSE, and LCCC values for EC prediction were only 0.79, 0.38 dS/m, and 0.88, respectively, suggesting relatively limited generalization ability. The overall ranking of predictive performance among the four prediction models followed a trend of PLSR > GPR $\approx$ SVR > RFR.

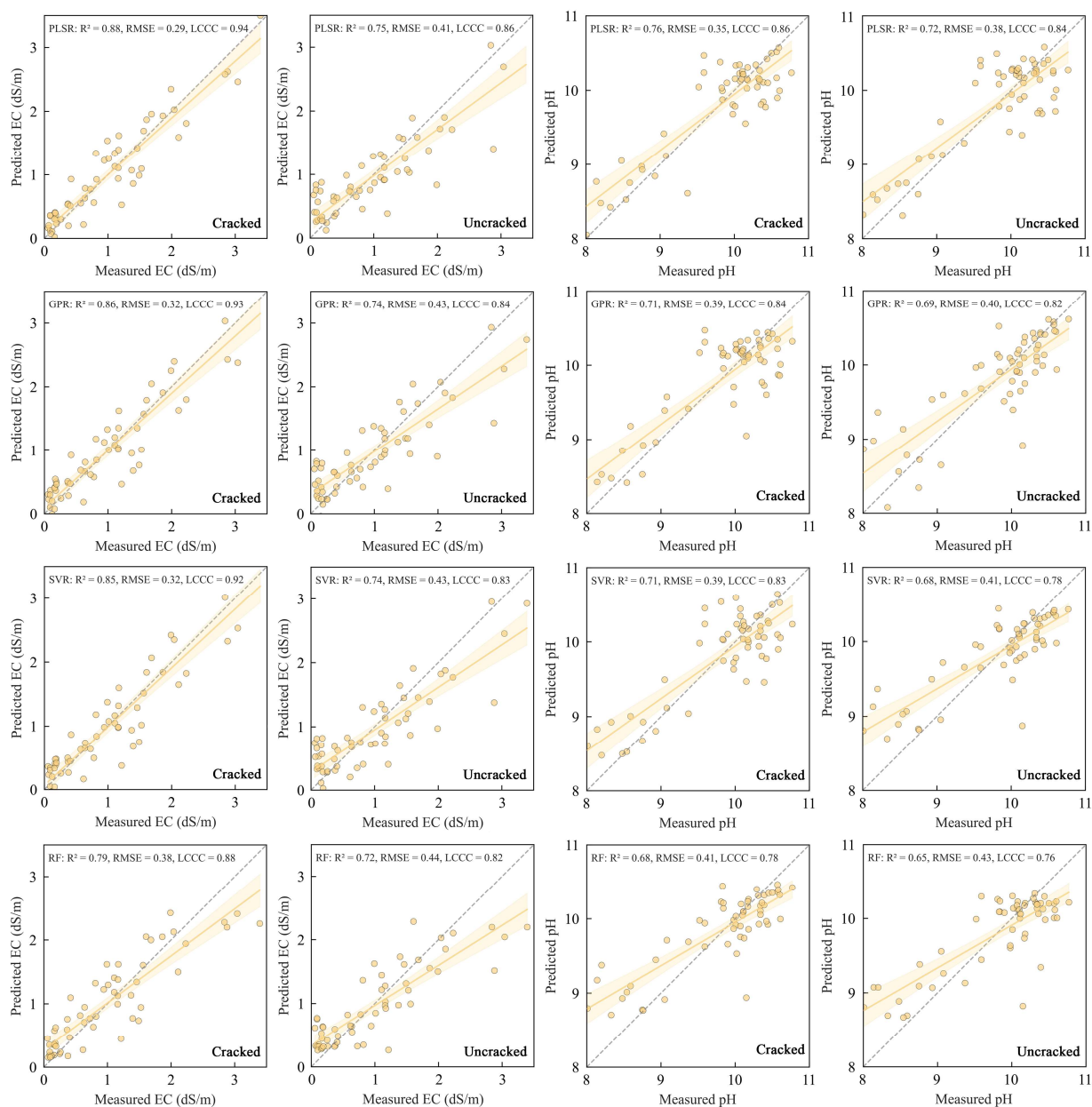


Figure 9. Scatter plots of measured and predicted salinity parameters.

4. Discussion

4.1. The Physical Mechanisms Governing the Impact of the Surface State on the Spectral Response

The saline–alkali soils of the Songnen Plain contain mostly non-swelling clay minerals with little spatial variation, indicating minimal influence of clay mineralogy on soil cracking [64]. Zhang et al. [65] clearly demonstrated, through shrinkage and cracking experiments conducted on soda-type saline–alkali soils in the Songnen Plain, that soil salinity is the primary controlling factor for soil shrinkage and cracking in this region, showing a significant positive correlation with cracking intensity. Furthermore, strongly alkaline conditions exacerbate colloidal dispersion, structural breakdown, and soil hardening, thereby further promoting cracking [66]. There is a clear correlation between soil salinity and its spectral characteristics, which serves as a key basis for hyperspectral remote sensing monitoring of soil salinization [67]. Salt stress induces varying degrees of changes in the soil's absorption and reflection properties at different wavelengths, establishing a spectral response mechanism for soil salinization. This provides both the physical foundation for remote sensing-based extraction of saline soil information and the core basis for remote sensing monitoring of soil salinization.

In this study, four models significantly outperform in predicting soil salinity under cracked surface compared to uncracked surface conditions. This is because desiccation cracks provide favorable observational conditions for directly obtaining salt-related information through optical remote sensing. Specifically, the crack structures modulate the propagation of electromagnetic radiation at the surface through the synergistic effects of geometric morphological characteristics and dielectric heterogeneity: on one hand, cracks increase macroscopic surface roughness, inducing scattering, diffraction, and shadowing effects of electromagnetic waves; on the other hand, spatial heterogeneity in the moisture and salt distribution between the crack interiors and surrounding areas leads to significant gradients in dielectric constants, forming strong dielectric interfaces that enhance electromagnetic energy absorption and attenuation, thereby altering radiation transmission paths and intensities. Furthermore, saline minerals not only promote the initial formation of desiccation cracks but also significantly increase crack width, depth, and spatial connectivity [68], thereby enhancing both interface scattering at the soil surface and volume scattering within the cracks. As crack regions expand, incident radiation undergoes more frequent non-specular reflections and multiple scattering attenuations at the surface, systematically reducing the effective radiant flux reaching the sensor, which manifests as a continuous decline in overall reflectance. Notably, the heterogeneous microtopography created by desiccation cracks substantially increases the complexity of the surface geometry, further amplifying spectral separability among salt-affected soil surfaces with varying crack density, orientation, and development stages, thus providing a physical mechanism foundation for retrieving soil salinity information [69].

4.2. The Advantages of FOD Processing (FOD + Multi-Dimensional Indices)

Compared to other mathematical transformation methods for processing hyperspectral data, traditional integer-order differentiation can enhance spectral features, though it often leads to the loss of some critical spectral information, making it difficult to meet the high-precision inversion requirements for soil information [70]. In contrast, fractional-order differentiation, with its continuous order property, enables more precise characterization of subtle changes in spectral reflectance at finer order scales, thereby preserving discriminative information from the original spectrum more completely and significantly improving the efficiency of spectral data utilization. Additionally, FOD can efficiently extract subtle spectral features closely related to soil properties from hyperspectral data, while effectively suppressing background noise interference and significantly correcting baseline drift

effects [71,72]. Its key advantage lies in enhancing the specificity and sensitivity of spectral responses to critical soil physicochemical parameters through continuously adjustable differentiation orders, thereby providing a physically interpretable and statistically robust spectral characterization foundation for the inversion of soil properties such as salinity, organic carbon, moisture and mineral content [73–75]. This study employs a FOD transformation with an order interval of 0.1. The results show that after this processing, the correlations between various fractional-order spectral indices and EC or pH are significantly enhanced compared to those of the original spectral reflectance. Further analysis reveals that surface physical conditions strongly influence the spatial distribution patterns of optimal differential orders for spectral indices: under both cracked and non-cracked surface conditions, the optimal orders for EC mainly concentrate around non-integer values near the first order, whereas those for pH predominantly occur at integer orders (especially the first and second order). This difference arises from the distinct spectral response mechanisms of EC and pH. Specifically, the spectral signals induced by soil salinity are weak, dispersed across bands, and highly susceptible to noise; integer-order differentiation, due to its large stepwise jumps in order, struggles to effectively capture such weak and non-stationary spectral perturbations [76]. In contrast, fractional-order differentiation can adaptively amplify subtle spectral fluctuations through an adjustable order [77].

Moreover, surface cracking exposes salts directly to the surface, leading to more uniform spectral responses, whereas on uncracked surfaces, surface crusts cause shielding and scattering effects on salt-related spectral signals, increasing the complexity of spectral disturbances [78,79], thus resulting in a more concentrated distribution of optimal orders for EC under cracked conditions. In comparison, pH primarily affects soil properties such as the colloid content and morphology of iron–aluminum oxides, inducing macroscopic and gradual changes in reflectance across the visible-to-near-infrared range [80]. These low-frequency, high-amplitude spectral responses can be adequately captured by first- or second-order integer differentiation. Additionally, the chemical properties of soil reflected by pH exhibit relatively low sensitivity to surface physical structures (such as cracking or crusting) [81], hence maintaining a high consistency in optimal differential orders across different surface conditions.

4.3. Performance of Different Prediction Models

This study systematically evaluated the predictive performance of four machine learning regression models (PLSR, GPR, SVR, and RFR) for estimating soil pH and EC under both cracked and uncracked surface conditions. The results in Figure 9 indicate that all models can achieve quantitative prediction of target salinity parameters to some extent; however, their accuracy and robustness vary depending on surface conditions and modeling mechanisms. Overall, PLSR demonstrated the best overall predictive performance, followed by GPR and SVR, which showed similar and significantly better accuracy than RFR. In contrast, RFR performed weakest under both surface conditions. A deep analysis of their modeling mechanisms reveals that PLSR achieves simultaneous dimensionality reduction and latent variable extraction by jointly decomposing the matrix of selected FOD spectral indices and the matrix of salt parameters, effectively alleviating the potential multicollinearity among the selected FOD spectral indices while requiring few soil samples and demonstrating strong model stability. In comparison, although GPR demonstrates strong adaptability to small sample sizes within the Bayesian framework, redundant information among spectral indices still interferes with the accurate estimation of the kernel covariance matrix, thereby limiting prediction accuracy. SVR is sensitive to the signal-to-noise ratio of input features and hyperparameter combinations, indicating that it may be insufficient to fully approximate the global optimal configuration through grid search or Bayesian

optimization under a limited sample size. Regarding the limited sample size, RFR suffers from reduced variability among base learners and weakened ensemble performance due to insufficient bootstrap sampling diversity and estimation bias introduced by feature selection, ultimately affecting the model's generalization ability and prediction robustness. Notably, the existing literature consistently confirms that PLSR can reliably establish quantitative relationships between spectral responses and soil physicochemical properties under sample-limited conditions, maintaining high prediction reliability [82–84].

4.4. Uncertainties and Limitations of the Study

As the results show in Figure 9, regardless of whether the surface is under a cracked or uncracked state, all models predict the pH with lower accuracy than the EC. This difference stems from the fundamental distinction in their spectral response mechanisms: EC's spectral response primarily arises from characteristic absorption by salt ions in the visible to near-infrared range, grounded in clear physicochemical principles, whereas pH, as an indirect indicator of H^+ activity in solution, lacks detectable spectral features such as molecular vibrations or electronic transitions. Its spectral signal must instead be indirectly reflected through intermediate variables such as mineral composition, organic matter content, and cation exchange capacity. Consequently, pH-related spectral responses generally exhibit low signal intensity and a poor signal-to-noise ratio.

Although this study provides scientifically meaningful empirical support for the remote sensing inversion of soil salinity parameters in saline–alkali lands of the Songnen Plain, several limitations remain. First, the current modeling and analysis are primarily based on ground-based spectral data collected within a local area, during fixed periods, and using specific sensors, and have not yet been systematically validated across different hyperspectral remote sensing platforms. Second, the limited sample size, when coupled with the joint processing of high-dimensional FOD spectral features, may increase the potential risk of spurious correlations, model overfitting, and inflated estimates of predictive accuracy. In addition, the transferability and applicability of the developed model in other typical saline–alkali regions are still unclear, necessitating systematic cross-validation across multiple regions and ecological gradients to clarify and define its scope. Therefore, future research should integrate multi-source, multi-scale, and multi-temporal remote sensing data to build more representative training and validation datasets, with a focus on developing transfer learning strategies for complex scenarios and frameworks for quantifying prediction uncertainty.

5. Conclusions

This study systematically evaluated the application potential of fractional-order derivative spectral transformation in predicting electrical conductivity (EC) and pH in soda saline–alkali soils across the Songnen Plain. After that, the key FOD spectral indices most sensitive to EC and pH were identified using the XGBoost + SHAP analysis. Subsequently, multiple machine learning models were developed and compared for predicting EC and pH under both cracked and uncracked surface conditions. The results showed that the FOD spectral indices processed exhibited significantly enhanced correlations with EC and pH. At the same salinity level, all models demonstrated a notably superior prediction accuracy, robustness, and generalization capability under cracked surface conditions compared to uncracked surface states, confirming that surface cracks effectively enhance the optical detectability of salinization information by amplifying the intensity and spatial heterogeneity of salinity-related spectral signals. Among the models, PLSR achieved the best fitting performance in EC inversion while its predictive ability for pH was still limited, reflecting the more complex spectral response mechanisms of pH influenced by multiple coupled

physicochemical factors. Future research should focus on expanding sample spatial coverage and improving the representativeness of salinity gradients, incorporating auxiliary variables such as mineral composition, organic matter content, and cation exchange capacity to strengthen the physical interpretability of pH modeling. Meanwhile, integrating large-scale, spatiotemporally continuous multi-source remote sensing data from satellite and aerial platforms will facilitate model scaling from field to regional levels, thereby supporting dynamic monitoring of saline–alkali lands.

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References

- Hou, D. Sustainable Remediation in China: Elimination, Immobilization, or Dilution. *Environ. Sci. Technol.* **2021**, *55*, 15572–15574. [[CrossRef](#)] [[PubMed](#)]
- Purdue, L.; Raibaldi, A.; Mazuy, A.; Costa, S. Can we detect soil salinity in ancient arid agricultural soils? A geoarchaeological, physico-chemical and micromorphological investigation (Oasis of Masafi, UAE). *J. Arid Environ.* **2026**, *232*, 105475.
- Aragues, R.; Urdanoz, V.; Cetin, M.; Kirda, C.; Daghari, H.; Ltifi, W.; Lahlou, M.; Douaik, A. Soil salinity related to physical soil characteristics and irrigation management in four Mediterranean irrigation districts. *Arg. Water Manag.* **2011**, *98*, 959–966. [[CrossRef](#)]
- Schillaci, C.; Scarpa, S.; Yunta, F.; Lipani, A.; Visconti, F.; Szatmári, G.; Balog, K.; Koganti, T.; Greve, M.; Bondi, G.; et al. Empirical estimation of saturated soil-paste electrical conductivity in the EU using pedotransfer functions and Quantile Regression Forests: A mapping approach based on LUCAS topsoil data. *Geoderma* **2025**, *454*, 117199. [[CrossRef](#)]
- Masoud, A.A.; Koike, K.; Atwia, M.G.; El-Horiny, M.M.; Gemail, K.S. Mapping soil salinity using spectral mixture analysis of landsat 8 OLI images to identify factors influencing salinization in an arid region. *Int. J. Appl. Earth Obs.* **2019**, *83*, 101944. [[CrossRef](#)]
- Hu, Y.; Yang, F.; Yang, N.; Jia, W.; Cui, Y. Analysis and Prospects of Saline-alkali Land in China from the Perspective of Utilization. *Chin. J. Soil Sci.* **2023**, *54*, 489–494. (In Chinese)
- Domsch, H.; Giebel, A. Estimation of soil textural features from soil electrical conductivity recorded using the EM38. *Precis. Agric.* **2004**, *5*, 389–409. [[CrossRef](#)]
- Grellier, S.; Florsch, N.; Camerlynck, C.; Janeau, J.L.; Podwojewski, P.; Lorentz, S. The use of Slingram EM38 data for topsoil and subsoil geoelectrical characterization with a Bayesian inversion. *Geoderma* **2013**, *200–201*, 140–155. [[CrossRef](#)]
- Heil, K.; Schmidhalter, U. Comparison of the EM38 and EM38-MK2 electromagnetic induction-based sensors for spatial soil analysis at field scale. *Comput. Electron. Agric.* **2015**, *110*, 267–280.
- Zarai, B.; Walter, C.; Michot, D.; Montoroi, J.P.; Hachicha, M. Integrating multiple electromagnetic data to map spatio temporal variability of soil salinity in Kairouan region, Central Tunisia. *J. Arid Land* **2022**, *14*, 186–202. [[CrossRef](#)]
- Paz, M.C.; Castanheira, N.L.; Paz, A.M.; Gonçalves, M.C.; Monteiro Santos, F.; Farzaman, M. Comparison of Electromagnetic Induction and Electrical Resistivity Tomography in Assessing Soil Salinity: Insights from Four Plots with Distinct Soil Salinity Levels. *Land* **2024**, *13*, 295. [[CrossRef](#)]

12. Autovino, D.; Coppola, A.; De Mascellis, R.; Farzamian, M.; Basile, A. An in-situ methodology to separate the contribution of soil water content and salinity to EMI-based soil electrical conductivity. *Soil* **2026**, *12*, 37–54.
13. Khongnawang, T.; Zare, E.; Srihabun, P.; Triantafilis, J. Comparing electromagnetic induction instruments to map soil salinity in two-dimensional crosssections along the Kham-rean Canal using EM inversion software. *Geoderma* **2020**, *377*, 114611.
14. Tazifor Tchantcho, M.; Zimmermann, E.; Huisman, J.A.; Dick, M.; Mester, A.; van Waasen, S. Low-Pass Filters for a Temperature Drift Correction Method for Electromagnetic Induction Systems. *Sensors* **2023**, *23*, 7322. [[CrossRef](#)] [[PubMed](#)]
15. Fahad, F.K.; Su, H.; Xu, L.; Jing, T. Soil salinity mapping in Everglades National Park using remote sensing techniques and vegetation salt tolerance. *Phys. Chem. Earth* **2019**, *110*, 31–50. [[CrossRef](#)]
16. Sutton, A.; Fisher, A.; Metternicht, G. A Systematic Review on Remote Sensing of Dryland Ecological Integrity: Improvement in the Spatiotemporal Monitoring of Vegetation Is Required. *Remote Sens.* **2026**, *18*, 184. [[CrossRef](#)]
17. Sutton, A.; Fisher, A.G.; Eldridge, D.J.; Metternicht, G. Multi-temporal remote sensing of ground cover reveals beneficial effects of soil carbon farming in a semi-arid landscape. *Comput. Electron. Agric.* **2025**, *234*, 110278.
18. Ivushkin, K.; Bartholomeus, H.; Bregt, A.K.; Pulatov, A.; Kempen, B.; de Sousa, L. Global mapping of soil salinity change. *Remote Sens. Environ.* **2019**, *231*, 111260. [[CrossRef](#)]
19. Kumar, P.; Tiwari, P.; Biswas, A.; Srivastava, P.K. Spatio-temporal assessment of soil salinization utilizing remote sensing derivatives, and prediction modeling: Implications for sustainable development. *Geosci. Front.* **2024**, *15*, 101881. [[CrossRef](#)]
20. Bouaziz, M.; Hihi, S.; Chtourou, M.; Osunmadewa, B. Soil Salinity Detection in Semi-Arid Region Using Spectral Unmixing, Remote Sensing and Ground Truth Measurements. *J. Geogr. Inf. Syst.* **2020**, *12*, 372–386.
21. Lazzeri, G.; Milewski, R.; Foerster, S.; Moretti, S.; Chabrilat, S. Early Detection of Soil Salinization by Means of Spaceborne Hyperspectral Imagery. *Remote Sens.* **2025**, *17*, 2486. [[CrossRef](#)]
22. Sahbeni, G.; Ngabire, M.; Musyimi, P.K.; Székely, B. Challenges and Opportunities in Remote Sensing for Soil Salinization Mapping and Monitoring: A Review. *Remote Sens.* **2023**, *15*, 2540. [[CrossRef](#)]
23. Wang, F.; Han, L.; Liu, L.; Bai, C.; Ao, J.; Hu, H.; Li, R.; Li, X.; Guo, X.; Wei, Y. Advancements and Perspective in the Quantitative Assessment of Soil Salinity Utilizing Remote Sensing and Machine Learning Algorithms: A Review. *Remote Sens.* **2024**, *16*, 4812. [[CrossRef](#)]
24. Das, A.; Bhattacharya, B.K.; Setia, R.; Jayasree, G.; Das, B.S. A novel method for detexting soil salinity using AVIRIS-NG imaging spectroscopy and ensemble machine learning. *ISPRS J. Photogramm.* **2023**, *200*, 191–212.
25. Ge, X.; Ding, J.; Teng, D.; Xie, B.; Zhang, X.; Wang, J.; Han, L.; Bao, Q.; Wang, J. Exploring the capability of Gaofen-5 hyperspectral data for assessing soil salinity risks. *Int. J. Appl. Earth Obs. Geoinf.* **2022**, *112*, 102969. [[CrossRef](#)]
26. Mahajan, G.R.; Das, B.; Gaikwad, B.; Murganekar, D.; Desai, A.; Morajkar, S.; Patel, K.P.; Kulkarni, R.M. Monitoring properties of the salt-affected soils by multivariate analysis of the visible and near-infrared hyperspectral data. *Catena* **2021**, *198*, 105041.
27. Abuzaid, A.S.; El-Komy, M.S.; Shokr, M.S.; El Baroudy, A.A.; Mohamed, E.S.; Rebouh, N.Y.; Abdel-Hai, M.S. Predicting Dynamics of Soil Salinity and Sodicity Using Remote Sensing Techniques: A Landscape-Scale Assessment in the Northeastern Egypt. *Sustainability* **2023**, *15*, 9440. [[CrossRef](#)]
28. Gorji, T.; Yildirim, A.; Hamzehpour, N.; Tanik, A.; Sertel, E. Soil salinity analysis of Urmia Lake Basin using Landsat-8 OLI and Sentinel-2A based spectral indices and electrical conductivity measurements. *Ecol. Indic.* **2020**, *112*, 106173. [[CrossRef](#)]
29. Abbas, J.A.A. Soil salinity assessment by using spectral salinity indices in Al-Sweira project middle of the Iraqi alluvial plain. *Int. J. Environ. Sci. Technol.* **2023**, *20*, 10847–10860.
30. Salem, O.H.; Jia, Z. Evaluation of Different Soil Salinity Indices Using Remote Sensing Techniques in Siwa Oasis, Egypt. *Agronomy* **2024**, *14*, 723. [[CrossRef](#)]
31. Zhou, X.; Zhang, F.; Liu, C.; Kung, H.; Johnson, V. Soil salinity inversion based on novel spectral index. *Environ. Earth Sci.* **2021**, *80*, 501. [[CrossRef](#)]
32. Pedrero Salcedo, F.; Pérez Cutillas, P.; Aziz, F.; Llobet Escabias, M.; Boesveld, H.; Bartholomeus, H.; Tallou, A. Soil Salinity Prediction Using Remotely Piloted Aircraft Systems under Semi-Arid Environments Irrigated with Salty Non-Conventional Water Resources. *Agronomy* **2022**, *12*, 2022.
33. Aboelsoud, H.M.; AbdelRahman, M.A.E.; Kheir, A.M.S.; Eid, M.S.M.; Ammar, K.A.; Khalifa, T.H.; Scopa, A. Quantitative Estimation of Saline-Soil Amelioration Using Remote-Sensing Indices in Arid Land for Better Management. *Land* **2022**, *11*, 1041.
34. Geng, J.; Lv, J.; Pei, J.; Liao, C.; Tan, Q.; Wang, T.; Fang, H.; Wang, L. Prediction of soil organic carbon in black soil based on a synergistic scheme from hyperspectral data: Combining fractional-order derivatives and three-dimensional spectral indices. *Comput. Electron. Agric.* **2024**, *220*, 108905.
35. Luo, Y.; Li, C.; Huang, J.; Dong, C.; Wang, J. Integrating fractional-order derivatives of soil and leaf hyperspectral reflectance for improved estimation of mangrove soil organic carbon. *Geoderma* **2025**, *458*, 117324. [[CrossRef](#)]

36. Bangelesa, F.; Adam, E.; Knight, J.; Dhau, I.; Ramudzuli, M.; Mokotjomela, T.M. Predicting soil organic carbon content using hyperspectral remote sensing in a degraded mountain landscape in Lesotho. *Appl. Environ. Soil Sci.* **2020**, *2020*, 2158573. [\[CrossRef\]](#)
37. Kawamura, K.; Tsujimoto, Y.; Nishigaki, T.; Andriamananjara, A.; Rabenarivo, M.; Asai, H.; Rakotoson, T.; Razafimbelo, T. Laboratory Visible and Near-Infrared Spectroscopy with Genetic Algorithm-Based Partial Least Squares Regression for Assessing the Soil Phosphorus Content of Upland and Lowland Rice Fields in Madagascar. *Remote Sens.* **2019**, *11*, 506.
38. Song, Y.; Zhao, X.; Su, H.; Li, B.; Hu, Y.; Cui, X. Predicting spatial variations in soil nutrients with hyperspectral remote sensing at regional scale. *Sensors* **2018**, *18*, 3086. [\[CrossRef\]](#) [\[PubMed\]](#)
39. Wei, L.; Yuan, Z.; Zhong, Y.; Yang, L.; Hu, X.; Zhang, Y. An improved gradient boosting regression tree estimation model for soil heavy metal (arsenic) pollution monitoring using hyperspectral remote sensing. *Appl. Sci.* **2019**, *9*, 1943. [\[CrossRef\]](#)
40. Tziolas, N.; Tsakiridis, N.; Ben-Dor, E.; Theocharis, J.; Zalidis, G. A memory-based learning approach utilizing combined spectral sources and geographical proximity for improved VIS-NIR-SWIR soil properties estimation. *Geoderma* **2019**, *340*, 11–24.
41. Wang, X.; Zhang, F.; Kung, H.; Johnson, V.C. New methods for improving the remote sensing estimation of soil organic matter content (somc) in the Ebinur Lake Wetland National Nature Reserve (ELWNNR) in northwest China. *Remote Sens. Environ.* **2018**, *218*, 104–118. [\[CrossRef\]](#)
42. Abdelouahab, M.; Hamri, N. The Grünwald–Letnikov fractional-order differential with fixed memory length. *Mediterr. J. Math.* **2016**, *13*, 557–572.
43. Obembe, A.D.; Abu-Khamsin, S.; Hossain, M.E.; Mustapha, K. Analysis of subdiffusion in disordered and fractured media using a Grünwald–Letnikov fractional calculus model. *Comput. Geosci.* **2018**, *22*, 1231–1250. [\[CrossRef\]](#)
44. Wang, J.; Ye, Y.; Gao, X. Fractional 90 phase-shift filtering based on the double-sided Grünwald–Letnikov differintegrator. *IET Signal Process.* **2015**, *9*, 328–334.
45. Karaagac, B. New exact solutions for some fractional order differential equations via improved sub-equation method. *Discret. Contin. Dyn. Syst.-S* **2019**, *12*, 447–454. [\[CrossRef\]](#)
46. Ge, X.; Wang, J.; Ding, J.; Cao, X.; Zhang, Z.; Liu, J.; Li, X. Combining UAV-based hyperspectral imagery and machine learning algorithms for soil moisture content monitoring. *PeerJ* **2019**, *7*, e6926. [\[CrossRef\]](#) [\[PubMed\]](#)
47. Hong, Y.; Guo, L.; Chen, S.; Marc, L.; Abdul, M.M.; Yu, L.; Chen, Y.; Liu, Y.; Liu, Y.; Cheng, H.; et al. Exploring the potential of airborne hyperspectral image for estimating topsoil organic carbon: Effects of fractional-order derivative and optimal band combination algorithm. *Geoderma* **2020**, *365*, 114228. [\[CrossRef\]](#)
48. Nawar, S.; Buddenbaum, H.; Hill, J. Estimation of soil salinity using three quantitative methods based on visible and near-infrared reflectance spectroscopy: A case study from Egypt. *Arab. J. Geosci.* **2015**, *8*, 5127–5140.
49. Jackson, R.D. Spectral indices in N_Space. *Remote Sens. Environ.* **1983**, *13*, 409–421.
50. Lao, C.; Yu, X.; Zhan, L.; Xin, P. Monitoring soil salinity in coastal wetlands with Sentinel-2 MSI data: Combining fractional-order derivatives and stacked machine learning models. *Agric. Water Manag.* **2024**, *306*, 109147. [\[CrossRef\]](#)
51. Ahmed, M.T.; Kamruzzaman, M. Enhancing corn quality prediction: Variable selection and explainable AI in spectroscopic analysis. *Smart Agric. Technol.* **2024**, *8*, 100458. [\[CrossRef\]](#)
52. Amiri, M.; Pourghasemi, H.R.; Ghanbarian, G.A.; Afzali, S.F. Assessment of the importance of gully erosion effective factors using Boruta algorithm and its spatial modeling and mapping using three machine learning algorithms. *Geoderma* **2019**, *340*, 55–69. [\[CrossRef\]](#)
53. Sui, Y.; Jiang, R.; Liu, Y.; Zhang, X.; Lin, N.; Zheng, X.; Li, B.; Yu, H. Predicting the spatial distribution of soil salinity based on multi-temporal multispectral images and environmental covariates. *Comput. Electron. Agric.* **2025**, *231*, 109970. [\[CrossRef\]](#)
54. Clerck, E.D.; Reyes-Munoz, P.; Prikaziuk, E.; Kovacs, D.D.; Verrelst, J. High-spatial-resolution gross primary production estimation from Sentinel-2 reflectance using hybrid Gaussian processes modeling. *ISPRS J. Photogramm. Remote Sens.* **2026**, *232*, 172–195.
55. Taghizadeh-Mehrjardi, R.; Schmidt, K.; Toomanian, N.; Heung, B.; Mosavi, A.; Band, S.S.; Amirian-Chakan, A.; Fathabadi, A.; Scholten, T. Improving the spatial prediction of soil salinity in arid regions using wavelet transformation and support vector regression models. *Geoderma* **2021**, *383*, 114793. [\[CrossRef\]](#)
56. Lamichhane, M.; Mehan, S.; Mankin, K.R. Soil moisture prediction using remote sensing and machine learning algorithms: A review on progress, challenges, and opportunities. *Remote Sens.* **2025**, *17*, 2397. [\[CrossRef\]](#)
57. Zhang, X.; Huang, B.; Liang, Z.; Sun, W.; Hu, W. Study on salinization characteristics of surface soil in Western Songnen Plain. *Soils* **2013**, *45*, 332–338. (In Chinese)
58. Hong, Y.; Shen, R.; Cheng, H.; Chen, Y.; Zhang, Y.; Liu, Y.; Zhou, M.; Yu, L.; Liu, Y. Estimating lead and zinc concentrations in peri-urban agricultural soils through reflectance spectroscopy: Effects of fractional-order derivative and random forest. *Sci. Total Environ.* **2019**, *651*, 1969–1982. [\[PubMed\]](#)

59. Wang, J.; Shi, T.; Liu, H.; Wu, G. Successive projections algorithm-based three-band vegetation index for foliar phosphorus estimation. *Ecol. Indic.* **2016**, *67*, 12–20.
60. Zhang, Z.; Ding, J.; Wang, J.; Ge, X. Prediction of soil organic matter in northwestern China using fractional-order derivative spectroscopy and modified normalized difference indices. *Catena* **2020**, *185*, 104257. [[CrossRef](#)]
61. Fastelli, M.; Zucchini, A.; Comodi, P.; Maturilli, A.; Alemanno, G.; Palomba, E.; Piergallini, R. NIR-MID Reflectance and Emissivity Study at Different Temperatures of Sodium Carbonate Minerals: Spectra Characterization and Implication for Remote Sensing Identification. *Minerals* **2021**, *11*, 845. [[CrossRef](#)]
62. Angelis, S.D.; Carli, C.; Tosi, F.; Beck, P.; Brissaud, O.; Schmitt, B.; Potin, S.; Sanctis, M.C.D.; Capaccioni, F.; Piccioni, G. NIR reflectance spectroscopy of hydrated and anhydrous sodium carbonates at different temperatures. *Icarus* **2019**, *317*, 388–411. [[CrossRef](#)]
63. Bertoluzza, A.; Monti, P.; Morelli, M.A.; Battaglia, M.A. A Raman and infrared spectroscopic study of compounds characterized by strong hydrogen bonds. *J. Mol. Struct.* **1981**, *73*, 19–29. [[CrossRef](#)]
64. Luo, X.; Zhang, X.; Zhang, L.; Guo, L.; Nie, Z.; Zhou, J.; Wang, R.; Zhang, T.; Miao, Y.; Ma, L.; et al. Characteristics of clay dispersion and its influencing factors in saline-sodic soils of Songnen Plain, China. *Agric. Water Manag.* **2024**, *303*, 109033. [[CrossRef](#)]
65. Zhang, Z.; Li, X.; Ren, J.; Zhou, S. Study on the drying process and the influencing factors of desiccation cracking of cohesive soda saline-alkali soil in the Songnen Plain, China. *Agriculture* **2023**, *13*, 1153. [[CrossRef](#)]
66. Tang, C.; Zhu, C.; Cheng, Q.; Zeng, H.; Xu, J.; Tian, B.; Shi, B. Desiccation cracking of soils: A review of investigation approaches, underlying mechanisms, and influencing factors. *Earth Sci. Rev.* **2021**, *216*, 103586.
67. Shokri, N.; Hassani, A.; Sahimi, M. Multi-scale soil salinization dynamics from global to pore scale: A review. *Rev. Geophys.* **2024**, *62*, e2023RG000804. [[CrossRef](#)]
68. Lima, L.A.; Grismer, M.E. Soil crack morphology and soil-salinity. *Soil Sci.* **1992**, *153*, 149–153. [[CrossRef](#)]
69. Dong, X.; Li, X.; Zheng, X.; Jiang, T.; Li, X. Effect of saline soil cracks on satellite spectral inversion electrical conductivity. *Remote Sens.* **2020**, *12*, 3392. [[CrossRef](#)]
70. Tian, A.; Zhao, J.; Tang, B.; Zhu, D.; Fu, C.; Xiong, H. Study on the Pretreatment of Soil Hyperspectral and Na⁺ Ion Data under Different Degrees of Human Activity Stress by Fractional-Order Derivatives. *Remote Sens.* **2021**, *13*, 3974. [[CrossRef](#)]
71. Hong, Y.; Liu, Y.; Chen, Y.; Liu, Y.; Yu, L.; Liu, Y.; Cheng, H. Application of fractional-order derivative in the quantitative estimation of soil organic matter content through visible and near-infrared spectroscopy. *Geoderma* **2019**, *337*, 758–769.
72. Lao, C.; Chen, J.; Zhang, Z.; Chen, Y.; Ma, Y.; Chen, H.; Gu, X.; Ning, J.; Jin, J.; Li, X. Predicting the contents of soil salt and major water-soluble ions with fractional-order derivative spectral indices and variable selection. *Comput. Electron. Agric.* **2021**, *182*, 106031.
73. Kahaer, Y.; Tashpolat, N.; Shi, Q.; Liu, S. Possibility of Zhuhai-1 Hyperspectral Imagery for Monitoring Salinized Soil Moisture Content Using Fractional Order Differentially Optimized Spectral Indices. *Water* **2020**, *12*, 3360. [[CrossRef](#)]
74. Khorram, M.; Sanyal, D.; Kumar, S. More than just spectra: The synergistic role of pH in advancing hyperspectral SOC prediction. *Catena* **2026**, *263*, 109712.
75. Cui, S.; Jiang, G.; Lu, J. Quantitative estimation of soil lithium content using fractional derivative spectroscopy and machine learning algorithms. *Opt. Laser Technol.* **2025**, *192*, 114057. [[CrossRef](#)]
76. Tian, A.; Zhao, J.; Tang, B.; Zhu, D.; Fu, C.; Xiong, H. Hyperspectral Prediction of Soil Total Salt Content by Different Disturbance Degree under a Fractional-Order Differential Model with Differing Spectral Transformations. *Remote Sens.* **2021**, *13*, 4283. [[CrossRef](#)]
77. Wang, Z.; Ding, J.; Tan, J.; Liu, J.; Zhang, T.; Cai, W.; Meng, S. UAV hyperspectral analysis of secondary salinization in arid oasis cotton fields: Effects of FOD feature selection and SOA-RF. *Front. Plant Sci.* **2024**, *15*, 1358965. [[CrossRef](#)] [[PubMed](#)]
78. Ren, J.; Li, X.; Li, S.; Zhu, H.; Zhao, K. Quantitative Analysis of Spectral Response to Soda Saline-Alkali Soil after Cracking Process: A Laboratory Procedure to Improve Soil Property Estimation. *Remote Sens.* **2019**, *11*, 1406.
79. Zhao, Y.; Zhang, Z.; Zhu, H.; Ren, J. Quantitative Response of Gray-Level Co-Occurrence Matrix Texture Features to the Salinity of Cracked Soda Saline-Alkali Soil. *Int. J. Environ. Res. Public Health* **2022**, *19*, 6556. [[PubMed](#)]
80. Ren, J.; Zhao, K.; Wu, X.; Zheng, X.; Li, X. Comparative Analysis of the Spectral Response to Soil Salinity of Saline-Sodic Soils under Different Surface Conditions. *Int. J. Environ. Res. Public Health* **2018**, *15*, 2721. [[CrossRef](#)] [[PubMed](#)]
81. Jia, P.; Shang, T.; Zhang, J.; Sun, Y. Inversion of soil pH during the dry and wet seasons in the Yinbei region of Ningxia, China, based on multi-source remote sensing data. *Geoderma Reg.* **2021**, *25*, e00399.
82. Lotfollahi, L.; Delavar, M.A.; Biswas, A.; Fatehi, S.; Scholten, T. Spectral prediction of soil salinity and alkalinity indicators using visible, near-, and mid-infrared spectroscopy. *J. Environ. Manag.* **2023**, *345*, 118854. [[CrossRef](#)]

83. El-Hamid, H.T.A.; Alshehri, F.; El-Zeiny, A.M.; Nour-Eldin, H. Remote sensing and statistical analyses for exploration and prediction of soil salinity in a vulnerable area to seawater intrusion. *Mar. Pollut. Bull.* **2023**, *187*, 114555. [[CrossRef](#)]
84. Farifteh, J.; Van der Meer, F.; Atzberger, C.; Carranza, E.J.M. Quantitative analysis of salt-affected soil reflectance spectra: A comparison of two adaptive methods (PLSR and ANN). *Remote Sens. Environ.* **2007**, *110*, 59–78. [[CrossRef](#)]

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