Spring Soil Salinity Retrieval and Validation in Typical Oasis Cotton Fields Based on Multispectral Remote Sensing: Postprint

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Abstract

To explore effective methods for rapid extraction of soil salinity in typical oasis cotton fields, obtain regional-scale characteristics and spatial distribution of soil salinization, and thereby provide references for soil salinization prevention and control. Taking the 31st Regiment of the Xinjiang Corps Agricultural Second Division as the study area, with spring Landsat 8 OLI multispectral images and field-measured soil salinity data from 2019 and 2021 as data sources, using band group, spectral index group, and full variable group as model input variable groups, employing Multiple stepwise regression (MSR), Partialleast squares regression (PLSR), Extreme learning machine (ELM), Support vector machine (SVM), and Back propagation neural network (BPNN) to construct remote sensing inversion models for soil salinity based on three input variable groups, investigating the influence of input variables and modeling methods on model accuracy, and determining the optimal spring soil salinity inversion model through comparison to quantitatively invert surface soil salinity. The results show: (1) The study area is mainly composed of non-salinized soil and lightly salinized soil, with a total sample coefficient of variation of 0.67, indicating moderate variability; the relationship between spectral reflectance and soil salinization degree demonstrates that the heavier the soil salinization, the higher the spectral reflectance. (2) Coastal band (b1), blue band (b2), green band (b3), red band (b4), and salinity indices (SI1, SI2, SI3, SI4, S3, S4, S5) all passed the significance test with $P<0.01$, with correlation coefficients all reaching above 0.4. (3) Among all models, the BPNN inversion model based on the full variable group achieved the highest accuracy, with R^2 of 0.705 for the modeling set and R^2 of 0.556 for the validation set. (4) According to the inversion results, the soils in the cultivated areas in spring 2019 and 2021 were mainly non-salinized soil, accounting for 55.55% and 64.62% of the total cultivated area respectively, followed by lightly salinized soil, accounting for 44.31%

and 35.17% respectively; the degree of soil salinization in 2021 was alleviated compared to 2019.

Full Text

Inversion and Validation of Soil Salinity in Typical Oasis Cotton Fields in Spring Based on Multispectral Remote Sensing

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Abstract

This study aimed to explore an effective method for rapidly extracting soil salinity from typical oasis cotton fields and to characterize the spatial distribution of soil salinization at the regional scale, thereby providing a reference for soil salinization control. The 31st Regiment of the 2nd Division of the Xinjiang Production and Construction Corps served as the study area. Using Landsat 8 OLI multispectral imagery and field-measured soil salinity data as data sources, we employed three input variable groups (band group, spectral index group, and full variable group) and five modeling approaches—multiple stepwise regression (MSR), partial least squares regression (PLSR), support vector machine (SVM), back propagation neural network (BPNN), and extreme learning machine (ELM)—to construct remote sensing inversion models for soil salinity. The effects of input variables and modeling methods on model accuracy were investigated, and the optimal spring soil salinity inversion model was identified through comparative analysis for quantitative estimation of surface soil salinity. The results demonstrated that: (1) The study area was dominated by non-salinized and slightly salinized soils, with a coefficient of variation of 0.67 for the total sample, indicating moderate variability. The relationship between spectral reflectance and soil salinization degree showed that higher soil salinization corresponded to greater spectral reflectance. (2) Significance tests ($P<0.01$) were conducted on the coastal band (b1), blue band (b2), green band (b3), red band (b4), and salinity indices SI1, SI2, SI3, SI4, S3, S4, and S5, with correlation coefficients all exceeding 0.4, indicating these parameters could represent soil salinity to a certain extent. (3) Among the six linear regression models, the MSR model based on the band group exhibited the best inversion performance, while the BPNN inversion model based on the full variable group achieved the highest accuracy. (4) According to the inversion results, soils in the spring of 2019 and 2021 were primarily non-salinized, accounting for 55.55% and 64.62% of the total cultivated area, respectively, followed by slightly salinized soils at 44.31% and 35.17%, respectively. Soil salinization in 2021 was alleviated compared with that in 2019.

Keywords: multispectral remote sensing inversion; soil salinity; spectral reflectance; variable group; machine learning

1. Introduction

Soil salinization has become a global ecological and environmental issue that severely restricts the sustainable development of irrigated agriculture in arid regions [1-3]. As a major agricultural reclamation area in China, Xinjiang has saline soil covering approximately one-third of its cultivated land, with salinization being particularly severe [4]. Consequently, there is an urgent need for rapid and accurate monitoring methods to track changes in soil salinity content, thereby supporting irrigation scheduling, salinization prevention and control, comprehensive utilization of saline-alkali land, and land management [5-6]. Traditional field sampling surveys consume substantial manpower and material resources and typically yield only point-scale information [7]. Remote sensing technology enables large-area acquisition of surface information, facilitates rapid access to multi-temporal data for the same region, and supports long-term soil salinization research. With its macroscopic, comprehensive, timely, dynamic, and low-cost characteristics, remote sensing has been widely applied for real-time monitoring of soil salinization and quantitative estimation of soil salinity [8-9].

With the increasing maturity of remote sensing technology, researchers have explored various methods to improve modeling accuracy, among which the construction of spectral parameters and selection of modeling methods have proven effective [10-12]. Many scholars have created model input variables using sensitive band combinations, characteristic spectral index construction, and spectral mathematical transformations [13-15]. For instance, Zhou et al. [16] constructed multiple vegetation and salinity indices based on Landsat 8 OLI multispectral imagery in the Ebinur Lake Wetland Nature Reserve, finding that the Enhanced Vegetation Index showed the highest correlation with soil salinity, followed by traditional vegetation indices, with salinity indices being the lowest. Zhang et al. [17] applied logarithmic, reciprocal, first-derivative, and second-derivative transformations to spectral data to enhance correlations with salinity and improve inversion accuracy. Zhang et al. [18] constructed spectral indices from MODIS imagery to invert soil salinity in the Yellow River Delta, while Alexakis et al. [19] calculated salinity indices from Landsat 8 OLI imagery for soil salinization monitoring in Crete, Greece, demonstrating that spectral indices were most sensitive to soil salinity. These studies indicate that screening sensitive spectral variables can effectively enhance model inversion performance [20].

In addition to independent variable optimization, modeling methods have evolved from traditional linear regression to machine learning algorithms with nonlinear fitting capabilities. Research has shown that when model input variables are numerous but weakly correlated with soil salinity, machine learning algorithms demonstrate greater advantages [21-22]. By comparing different models, researchers have identified the most suitable modeling methods for specific study areas, thereby improving remote sensing inversion accuracy. Feng et al. [23] compared traditional regression and machine learning algorithms, finding that the Back Propagation Neural Network (BPNN) model achieved optimal prediction performance with superior stability and accuracy compared with empirical regression models. Liu et al. [24] used Landsat 8 OLI imagery to construct soil salinity inversion models using multiple linear regression and BPNN, concluding that the nonlinear fitting capability of machine learning yielded higher inversion accuracy. Zhang et al. [25] found that the Support Vector Machine (SVM) model achieved the highest precision in the Hetao Irrigation District of Inner Mongolia, followed by quantile regression, with Partial Least Squares Regression (PLSR) being the lowest. These studies collectively demonstrate the superiority of machine learning algorithms in soil salinity remote sensing inversion.

Although previous soil salinization research has achieved satisfactory results, most remote sensing inversion studies have been based on imagery from a single period, reflecting only local salinization conditions at that time and limiting model generalizability. Moreover, salinization degree varies spatiotemporally, with soil salinity differing across locations. Therefore, investigating soil salinization conditions across different years in a given region is crucial [26]. In this context, this study selected the 31st Regiment of the 2nd Division of the Xinjiang Production and Construction Corps as the research area. Based on Landsat 8 OLI satellite imagery and corresponding surface soil salinity data, we employed Multiple Stepwise Regression (MSR), Extreme Learning Machine (ELM), BPNN, SVM, and PLSR to construct remote sensing inversion models for soil salinity in cotton fields, aiming to achieve quantitative inversion of cotton field soil salinity and provide a reference for real-time monitoring of surface soil salinity in the region.

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1. Materials and Methods

1.1 Study Area Overview

The 31st Regiment of the 2nd Division of the Xinjiang Production and Construction Corps is located at the southern foothills of the Tianshan Mountains, on the northeastern edge of the Tarim Basin, in the alluvial plain at the lower reaches of the Tarim and Kongque Rivers, within Yuli County, Bayingolin Mongol Autonomous Prefecture. It borders the Taklamakan Desert to the southwest and the Kumtag Desert to the northeast, with geographical coordinates of 39°30 -42°20 N, 85°24 -88°30 E. The main soil types in the irrigation district are saline soil, alkaline soil, and aeolian sandy soil. Situated deep in the Eurasian interior, the regiment experiences a temperate continental desert climate with large interannual precipitation variation, averaging 53.3-62.7 mm annually. The multi-year average evaporation is 2273–2788 mm. The existing irrigated area is 7.5$\times10^{4}$ hm^2, with drip irrigation under plastic film as the primary method. Irrigation water is sourced from the Tarim River and Qiala Reservoir, with seasonal irrigation of 2700-3450 $m^3 \cdot hm^{-2}$ beginning in April each year and winter irrigation of approximately 3600 $m^3 \cdot hm^{-2}$ using flood irrigation starting in November. The groundwater table is maintained at 1-3 m, with mineralization of 2-7 $g \cdot L^{-1}$; the Tarim River and reservoir water mineralization is 0.47–1.53 $g \cdot L^{-1}$; and irrigation drainage mineralization is 10.58–18.36 $g \cdot L^{-1}$.

1.2 Field Data Collection and Processing

Field sampling was conducted before cotton sowing (April 15–20) during the bare soil period when vegetation effects were minimal. After field reconnaissance, sampling points were arranged along the main canals from the reservoir intake, considering traffic conditions, distribution locations, and soil types. The final numbers of sampling points collected in 2019 and 2021 were 45 and 50, respectively.

1.2.1 Surface Soil Salinity Measurement Given the strong spatial variability of soil water and salt, an additional point was selected within a 10 m radius of each predetermined point. Surface soil (0–20 cm) was collected using a five-point sampling method, mixed using the quartering method as one sample for that location, and placed in labeled ziplock bags. A GPS device recorded the latitude and longitude of each point, and photographs documented salinization degree, crop type, and vegetation coverage. Soil samples were brought to the laboratory, where debris was removed, and the samples were air-dried and ground. A 10 g subsample was weighed and mixed with water at a 1:5 soil-water ratio in a conical flask, stirred with a glass rod, shaken for 10 minutes on a shaker to fully dissolve salts, and left to stand before measuring the electrical conductivity (EC) of the soil suspension ($S \cdot cm^{-1}$) using a conductivity meter. Soil total salt content ($g \cdot kg^{-1}$) was calculated using the empirical formula: $y = 0.0051x + 0.0534$ ($R^2 = 0.9534$).

1.2.2 Surface Soil Spectral Curve Acquisition and Processing Spectral measurements were conducted on clear, cloudless, windless days between 12:00-16:00. A PP Systems UniSpec spectrometer (310–1130 nm) was used to measure soil spectral reflectance. Before observation, standard whiteboard scanning and dark scanning were performed. The probe was positioned 15 cm above the ground to narrow the field of view and minimize background interference. Multiple spectral curves were measured for different salinization levels, with five replicates per level averaged to obtain measured hyperspectral data for each salinization grade. Post-processing using Origin 2018 and Multispec 5.1.5 software yielded soil spectral reflectance curves for 310–1130 nm.

1.3 Remote Sensing Image Acquisition and Processing

Landsat 8 OLI multispectral data were obtained from the United States Geological Survey (USGS) website (https://earthexplorer.usgs.gov/), with path/row 143/031, spatial resolution of 30 m, and revisit period of 16 days. Based on the principles of minimal cloud cover and proximity to sampling dates, images from April 21, 2019, and April 24, 2021, were selected as the multispectral data sources. ENVI 5.3 software was used for radiometric calibration, atmospheric correction, and clipping to convert digital numbers to radiance and then to surface reflectance. ArcGIS 10.2 and Excel were used to extract multispectral reflectance values at sampling points and calculate various spectral indices.

1.4 Spectral Parameter Construction

This study selected seven salinity indices as candidate input variables for the soil salinity inversion model. Spectral parameters and their formulas are shown in , where b1, b2, b3, b4, R, NIR, SWIR1, and SWIR2 represent reflectance of the coastal, blue, green, red, near-infrared, shortwave infrared 1, and shortwave infrared 2 bands, respectively. SI1–SI4 and S3–S5 are all salinity indices.

1.5 Remote Sensing Inversion Model Construction

Considering that soil salinity is affected by moisture and that irrigation, temperature, and precipitation vary between periods, the spatial variability of spring soil salinity distribution differs across years. After removing outliers, spring sample data from 2019 and 2021 were combined and sorted by soil salinity content. Samples were selected at equal intervals according to a 3:1 ratio for modeling and validation sets [27], yielding 72 modeling samples and 24 validation samples.

Pearson correlation analysis was conducted between image bands, salinity indices, and soil salinity content for the modeling set. Characteristic spectral parameters were screened and divided into three groups: band group, spectral index group, and full variable group, which served as input variables for modeling using five methods:

1) Multiple Stepwise Regression (MSR): An improved version of multiple linear regression that optimizes formulas to determine the contribution of each independent variable, 剔除不重要的变量 [15,21]. MSR modeling and analysis were performed using IBM SPSS Statistics 25.

2) Partial Least Squares Regression (PLSR): A multivariate regression method that eliminates multicollinearity among parameters through iterative processes [15,23]. The Unscrambler X 10.4 software was used for modeling and analysis.

3) Extreme Learning Machine (ELM): A single-hidden-layer feedforward neural network with strong generalization capability, minimal manual intervention, and fast learning speed [24]. Input-hidden layer weights and hidden neuron thresholds are randomly generated [28]. MATLAB 2018 was used for model construction. After repeated testing, the optimal network structures were determined as: band group (4-8-1), spectral index group (7-10-1), and full variable group (11-15-1).

4) Support Vector Machine (SVM): Based on establishing an optimal classification hyperplane that maximizes the margin [29]. For nonlinear problems, SVM maps data to high-dimensional space using kernel functions. This study used LIBSVM in MATLAB 2018. The kernel type was set to regression with a Gaussian radial basis function. Parameters c (cost) and g (kernel parameter) were tested against sample data, yielding: band group (c=0.5, g=0.25), spectral index group (c=1, g=0.125), and full variable group (c=1, g=0.125).

5) Back Propagation Neural Network (BPNN): A supervised learning model with strong self-organization and adaptive capabilities that can simulate any nonlinear input-output relationship [30]. This study used MATLAB 2018 with the following parameters: training function trainlm, hidden layer transfer function tansig, output layer function purelin, maximum iterations of 1000, and minimum error target of 0.0001. After repeated training, the optimal structures were: band group (4-10-1), spectral index group (7-12-1), and full variable group (11-18-1).

1.6 Model Evaluation Metrics

Model fitting capability was quantified using the coefficient of determination (R^2) and root mean square error (RMSE) to comprehensively evaluate modeling and validation performance [31]. R^2 closer to 1 indicates better model fit, while smaller RMSE indicates smaller errors between measured and predicted values. Thus, higher R^2 and lower RMSE signify higher model accuracy and better inversion performance.

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2. Results and Analysis

2.1 Soil Salinity Characteristics

According to Xinjiang soil salinization classification standards [32], soils were categorized into three grades: non-salinized (0–3 $g \cdot kg^{-1}$), slightly salinized (3–6 $g \cdot kg^{-1}$), and moderately salinized (6–10 $g \cdot kg^{-1}$). Descriptive statistical analysis of soil salinity is presented in . The total sample results showed proportions of 64.94% non-salinized, 27.27% slightly salinized, and 7.79% moderately salinized soils, with a coefficient of variation of 0.67, indicating moderate variability in cotton field soil salinity.

2.2 Measured Hyperspectral Characteristics

Soil hyperspectral wavelength range was 310–1130 nm. Different surface soil salinity contents resulted in varying soil reflectance, though spectral curves for different salinization grades were relatively parallel with similar morphology and consistent trends. As wavelength increased, soil hyperspectral reflectance first decreased then increased. From 310–373 nm, reflectance decreased rapidly with increasing wavelength; from 373–1130 nm, reflectance increased with wavelength, with slower growth in 373–1050 nm and rapid increase beyond 1050 nm. Overall, more severe soil salinization corresponded to higher spectral reflectance [Figure 2: see original paper].

2.3 Characteristic Spectral Parameter Optimization

Based on the Pearson correlation coefficient table [33], when sample size (n) equals 72, correlation coefficients (r) with absolute values greater than 0.4 are significant at the 0.01 level. Correlation coefficients between spectral parameters and soil salinity are shown in . Sensitive bands (P<0.01) and sensitive spectral indices (P<0.01) were selected, with all r values exceeding 0.4. The correlation magnitude with soil salinity was b1>b2>b3>b4, and for salinity indices: S3>SI2>SI4>S4>S5>SI1>SI3, all reaching significance at P<0.01, indicating these parameters could characterize soil salinity.

2.4 Soil Salinity Inversion Model Construction

The four significant bands (b1, b2, b3, b4) constituted the band group, while the seven significant salinity indices formed the spectral index group. To avoid omitting important spectral parameters and consider effects of different parameter categories, all 11 sensitive bands and indices were combined as the full variable group for modeling.

2.4.1 Soil Salinity Regression Models As shown in , when using the same variable group as input, all six models achieved R^2>0.4 for the modeling set, indicating good performance. During validation, the band group and spectral index group showed R^2>0.4 and RMSE<1.5, demonstrating satisfactory validation. Among the three machine learning algorithms, ELM achieved the highest modeling set R^2, reaching 0.70, followed by SVM, with BPNN showing the lowest accuracy. During validation, the band group and spectral index group exhibited larger RMSE values. The full variable group achieved the highest validation R^2 values, all exceeding 0.5, with RMSE<1.5, indicating good validation performance. Comprehensive comparison revealed that the BPNN model based on the full variable group was the optimal soil salinity inversion model among all candidates, with modeling set R^2 of 0.73 and validation set R^2 of 0.57.

2.4.2 Machine Learning Models As shown in , when band group and spectral index group served as inputs, all machine learning models achieved R^2>0.4

for the modeling set. The full variable group yielded modeling set R^2>0.5, with ELM reaching the highest value at 0.73. During validation, band group and spectral index group showed R^2>0.4 with RMSE<1.5. The full variable group achieved the highest validation R^2 values, all exceeding 0.5, with RMSE<1.5. Comprehensive comparison identified the BPNN model based on the full variable group as the optimal soil salinity inversion model, with modeling set R^2 of 0.73 and validation set R^2 of 0.57. Comparison of and revealed that machine learning models consistently outperformed linear regression models in accuracy. Therefore, the final BPNN model based on the full variable group was selected to invert surface soil salinity in spring.

2.5 Spatial Distribution of Soil Salinity Inversion

According to the inversion results, soils with salinity >6 $g \cdot kg^{-1}$ were distributed in the saline-alkali belt in the central irrigation district, while soils with salinity <3 $g \cdot kg^{-1}$ were located in areas far from wasteland within the irrigation district. Salinity increased with proximity to wasteland. The inversion results were consistent with Kriging interpolation results and field investigations, indicating high accuracy in cultivated land salinity inversion [Figure 3: see original paper] and [Figure 4: see original paper].

As shown in , non-salinized soils in spring 2019 and 2021 accounted for 55.55% and 64.62% of the total cultivated area, respectively, with 0–1 $g \cdot kg^{-1}$ soils showing the smallest distribution area, 1-2 $g \cdot kg^{-1}$ soils the next largest, and 2–3 $g \cdot kg^{-1}$ soils the largest area. Slightly salinized soils accounted for 44.31% and 35.17% of the area, respectively, with 5–6 $g \cdot kg^{-1}$ soils showing the smallest distribution, 4–5 $g \cdot kg^{-1}$ soils the next largest, and 3–4 $g \cdot kg^{-1}$ soils the largest area. Comparison of salinization degrees between years revealed that non-salinized soil area in 2021 increased by 9.07% compared with 2019, while slightly salinized soil area decreased by 9.14%, and moderately salinized soil area showed minimal change. Soils with salinity <2 $g \cdot kg^{-1}$ were mainly distributed near Qiala Reservoir and in the central and southeastern parts of the cultivated area. Salinity increased with proximity to wasteland on both north and south sides, with small patches in the northeast showing higher salinity, primarily slightly salinized. Moderately salinized soils were mainly distributed in the central saline belt, coinciding with actual image locations. The orange-red regions representing salinity >6 $g \cdot kg^{-1}$ shrank in 2021 compared with 2019, indicating reduced salinization. Overall, soil salinization in 2021 was alleviated compared with 2019.

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3. Discussion

3.1 Saline Soil Characteristics and Spectral Parameter Optimization

Cotton field soil salinity showed moderate variability, indicating susceptibility to natural factors (climate, topography, hydrology, geology) and anthropogenic factors (irrigation, tillage, fertilization) [34]. Sampling was conducted in spring when natural environments varied significantly between years. Combining spring data from both years helped neutralize interannual sample variability before splitting into modeling and validation sets, enhancing rationality. Correlation analysis between Landsat 8 OLI bands, spectral indices, and measured soil salinity revealed that sensitive multispectral bands were blue, green, and red, consistent with Sun et al. [35] and indicating that the 430–760 nm range contains abundant spectral information about soil salinity. Constructing characteristic spectral indices from band groups can 挖掘光谱与盐分之间的隐含信息, advancing quantitative remote sensing inversion of soil salinity. Wang et al. [36] and Bian et al. [37] found correlations between spectral indices and soil salinity, demonstrating their significant contribution to estimation applications. This study similarly showed that combining sensitive bands and sensitive spectral indices as model inputs yielded optimal modeling and validation performance.

3.2 Soil Salinity Inversion Model Establishment

Three variable groups and five methods were used to establish 15 soil salinity inversion models, revealing that different input variables and modeling methods affected model accuracy. Machine learning models consistently outperformed traditional linear regression in precision and stability due to the complex nonlinear relationship between soil salinization characteristics and surface soil salinity, which machine learning algorithms can effectively simulate. Many studies have confirmed the superior performance of machine learning algorithms [14,23], consistent with our findings. Feng et al. [23] found BPNN optimal for simulating total salt content, while our study identified BPNN as the best among three linear regression models and the overall optimal model. Although traditional linear regression performed less well than machine learning, its simplicity and clear regression equations offer practical value. Machine learning models can significantly improve accuracy but require parameter optimization, which demands substantial time and effort. Nevertheless, exploring the effects of different variable combinations and modeling methods on inversion accuracy remains valuable.

3.3 Spatiotemporal Variation Characteristics of Soil Salinity

Kriging interpolation maps are generated from point-scale measured salinity data, yielding coarse results that only approximate spatial distribution. Remote sensing technology can convert spectral reflectance at all image pixels to soil salinity using inversion models, achieving quantitative results. Pixel values can then be classified to determine counts and proportions at different salinity levels. Comparison of salinization between 2019 and 2021 revealed reduced severity in 2021, possibly related to temperature, evaporation, and irrigation amount. Higher temperatures enhance evaporation and salt transport to the surface, while greater irrigation amounts increase leaching and reduce surface salinity. The local government has also implemented reasonable irrigation and drainage systems and measures for saline soil management, achieving positive results over time.

Most existing research has focused on salinized soil inversion for a single year [38-39]. However, due to variable environmental conditions and complex land cover types within pixels, remote sensing imagery differs substantially between years. This study considered interannual environmental variability by incorporating spring data from two years, adjusting model parameters to establish an optimal inversion model that achieved good performance for spring soil salinity. However, the study focused on non-vegetated soils and did not invert soil salinity during the crop growth period. Future research should explore relationships between crop spectra and soil salinity. Additionally, the complex natural factors in the study area limit real-time monitoring, so the applicability of this inversion method to other regions and seasons requires further investigation.

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4. Conclusions

1) Cotton field soils were primarily non-salinized and slightly salinized, with a total sample coefficient of variation of 0.67, indicating moderate variability. The relationship between spectral reflectance and soil salinization degree showed that more severe salinization corresponded to higher spectral reflectance.

2) Correlation analysis between soil salinity and Landsat 8 OLI bands and spectral indices revealed that coastal, blue, green, and red bands and salinity indices SI1, SI2, SI3, SI4, S3, S4, and S5 all passed significance tests ($P<0.01$), with correlation coefficients exceeding 0.4.

3) Among all models, the BPNN model based on the full variable group achieved the highest inversion accuracy, with modeling set R^2 of 0.73 and validation set R^2 of 0.57. Based on comprehensive analysis of modeling and validation performance, the full variable group-based BPNN model was selected to invert surface soil salinity in spring cotton fields.

4) Inversion results indicated that soils in spring 2019 and 2021 were primarily non-salinized, accounting for 55.55% and 64.62% of total cultivated area, respectively, followed by slightly salinized soils at 44.31% and 35.17%, respectively. Soils closer to wasteland on north and south sides showed higher salinity, with small northeastern plots exhibiting elevated salinity. Soil salinization in 2021 was alleviated compared with 2019.

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Note: Figure translations are in progress. See original paper for figures.