



Article

Soil Salinity Inversion Model of Oasis in Arid Area Based on UAV Multispectral Remote Sensing

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Abstract: Soil salinization severely restricts the development of global industry and agriculture and affects human beings. In the arid area of Northwest China, oasis saline-alkali land threatens the development of agriculture and food security. This paper develops and optimizes an inversion monitoring model for monitoring the soil salt content using unmanned aerial vehicle (UAV) multispectral remote sensing data. Using the multispectral remote sensing data in three research areas, the soil salt inversion models based on the support vector machine regression (SVR), random forest (RF), backpropagation neural network (BPNN), and extreme learning machine (ELM) were constructed. The results show that the four constructed models based on the spectral index can achieve good inversion accuracy, and the red edge band can effectively improve the soil salt inversion accuracy in saline-alkali land with vegetation cover. Based on the obtained results, for bare land, the best model for soil salt inversion is the ELM model, which reaches the determination coefficient (R_v^2) of 0.707, the root mean square error $RMSE_v$ of 0.290, and the performance deviation ratio (RPD) of 1.852 on the test dataset. However, for agricultural land with vegetation cover, the best model for soil salinity inversion using the vegetation index is the BPNN model, which achieves R_v^2 of 0.836, $RMSE_v$ of 0.027, and RPD of 2.100 on the test dataset. This study provides technical support for rapid monitoring and inversion of soil salinization and salinization control in irrigation areas.

Keywords: soil salt content; UAV; multispectral image data; remote sensing inversion model



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1. Introduction

Soil salinization has been one of the most severe soil problems affecting the ecological environment, which significantly restricts the protection and development of the regional ecological environment [1–3]. Soil salinization of cultivated land can cause land degradation, destroy crop growth, and restrict the agricultural and economic development of arid areas in Northwest China [4–6]. Rapidly and accurately obtaining information on soil salt content can effectively evaluate the soil salinization degree and promote the sustainable development and utilization of salinized land. The traditional method of obtaining information on soil salt content is fixed-point sampling, which uses data measured by a conductivity meter [7–10]; however, this method is time-consuming and laborious [11]. In recent years, with a combination of remote sensing technology and agriculture, remote sensing technology has become a low-cost way to achieve fast information acquisition [12–14]. Remote sensing monitoring has been increasingly used in soil salinization measurement [15–19] combined the soil field spectrum and remote sensing image with the measured data of soil salinity and introduced the soil salt estimation and inversion method using remote sensing, which represents an effective and feasible method for estimation of regional soil salt content.

Satellite remote sensing data have often been used for monitoring soil salinization [20,21]. Allbed [2] calculated 13 spectral indices using the 4-band spectra of IKONOS satellite

remote sensing images. The results show that the spectral index calculated by the spectral band of satellite remote sensing can effectively analyze and predict the soil salinization degree. The combination of unmanned aerial vehicle (UAV) based remote sensing and soil salinization monitoring has attracted great attention recently. The UAV is easy to deploy, and the cost of remote sensing data acquisition is low, which can supplement the satellite remote sensing data [22,23]. A UAV can use different sensors in visible, infrared, and microwave bands, ensuring high-precision and rapid estimation of the soil salt content data in cultivated land [24,25]. The UAV multispectral remote sensing can rapidly and effectively monitor soil salinization by establishing a soil salinity inversion model [4]. It can improve the accuracy of soil salt content monitoring using the calculated salinity index, vegetation index, and other parameters [21,26]. Fan [27] collected multispectral soil salt content data in the Yellow River Delta, China, and established a soil salt inversion model. The results have proven the effectiveness of using the multispectral data in soil salt inversion [28].

When there is crop cover on the cultivated land, the irrigation method can be adjusted according to the real-time soil salinity information of the cultivated land to improve the crop yield. For saline cultivated land covered with crops, it is impossible to obtain the spectral reflectance of a soil surface directly by the UAV multispectral camera. Therefore, to improve the inversion accuracy of soil salt in cultivated land, many studies have introduced the red edge band, which can extract new band information, obtain the spectral reflectance of vegetation canopy, and calculate an improved spectral index by replacing the red edge band with the red light band [2,29]. Zheng [30] realized the monitoring of wheat stripe rust using the new vegetation index constructed in the red edge band. Zhang [31] calculated 20 vegetation indices using the red edge band and divided them into two groups, with or without the red edge spectral band. The results have shown that the classification accuracy can be improved by 7% using the red edge spectral band index. Wang [32] introduced the spectral index calculated in the red edge band for soil salinity inversion and achieved good inversion accuracy. Therefore, the red edge band can establish a nonlinear relationship with the soil salinity of cultivated land under vegetation and mine more spectral information, providing higher accuracy for the soil salt inversion of saline cultivated land covered by crops on a regional scale.

The multispectral inversion of soil salt content by a UAV has been mostly focused on bare land without crop cover. There are many types of saline-alkali lands covered by different crops in the arid oasis irrigation area of Northwest China, and the soil salt distribution beneath different crop covers is different. However, there has been less research on the soil salt content inversion of saline-alkali land under different crop covers. Therefore, this paper uses the saline-alkali land under different cover represented by bare land, alfalfa cover, and wheat cover in the arid oasis area as a study area and obtains multispectral remote sensing images by a UAV. In addition, the soil salt content data are collected, the red edge band is used to extract the band spectral reflectance and spectral index, and the correlation analysis is performed on the measured soil salt content. The soil salt inversion models of support vector machine (SVM), random forest (RF), backpropagation neural network (BPNN), and ELM under different crop covers are constructed. The precision of the established soil salt content models are evaluated and compared, and the best model of soil salt content for different crop mulches and the best algorithm model for the same research area are selected. This study provides a theoretical basis for developing accurate soil salinization monitoring and inversion models covered by different crops on a farm.

2. Materials and Methods

2.1. Study Area

The Belt and Road Initiative is located in Jiu Quan city, the Gansu province, China. Tao Lai River Basin is located in the west of Hexi Corridor, and it represents a sub-water system in the west of Hei River. Bian Wan Farm is a typical agricultural irrigation area in arid and semi-arid areas of low and middle latitudes. The total land area of the farm is 26.134 km², including 9.07 km² of cultivated land and more than 3.5 km² of water area. It is

an important food production base in the Hexi corridor. It has superior natural conditions, flat terrain, long hours of sunshine, and a large temperature difference between day and night. It is an excellent agricultural area for growing agricultural products. The central coordinates of the study area are $98^{\circ}30'36.36''\text{E}$ and $39^{\circ}50'0.38''\text{N}$. The multispectral and field sampling area of a UAV is the Bian Wan farm in the irrigation area of the Taolai River Basin is shown in Figure 1.

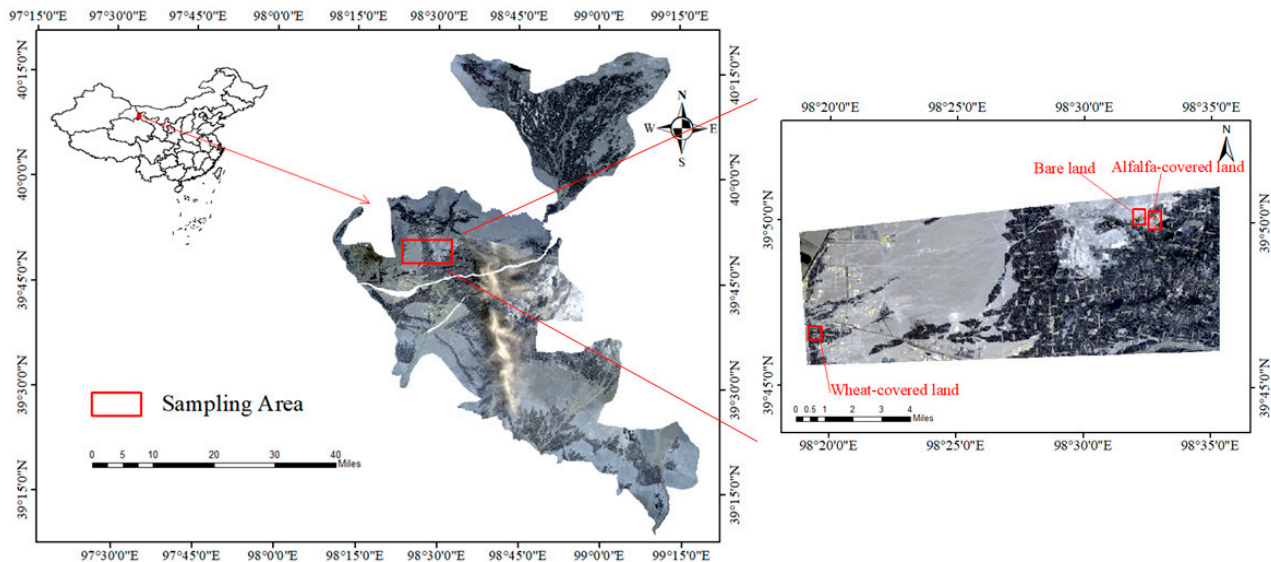


Figure 1. The geographical location of the study area.

2.2. UAV Remote Sensing Data Acquisition

The UAV remote sensing platform used in this study is the DJI P4 multispectral version produced by the Da Jiang company. Dajiang Zhitu and ENVI 5.6 are used for remote sensing image data processing. The multispectral camera uses six 1/2.9-inch CMOS image sensors. One color sensor is used for conventional visible light (RGB) imaging, and the remaining five monochrome sensors are used for multispectral imaging, including the near-infrared band. The parameters of the DJI P4 multispectral version are shown in Table 1. The flight altitude of the UAV is 100 m, the shooting mode is equal time interval photography, the flight speed is 7 m/s, the image overlap rate is 80%, and the image GSD is 5.3 cm/pixel.

Table 1. The parameters of the multispectral UAV.

Parameter	Size
Take-off weight/g	1487
PTZ rotation range/ $^{\circ}$	$-90^{\circ} \sim +30^{\circ}$
Image Resolution	1600×1300
Band and bandwidth/nm	B $450 \text{ nm} \pm 16 \text{ nm}$
	G $560 \text{ nm} \pm 16 \text{ nm}$
	R $650 \text{ nm} \pm 16 \text{ nm}$
	RedEdge $730 \text{ nm} \pm 16 \text{ nm}$
	NIR $840 \text{ nm} \pm 26 \text{ nm}$

Considering different salinization degrees in the Bian Wan farm, three representative land use land covers, namely bare land, spring wheat-covered land, and spring alfalfa-covered land, were selected for analysis, as shown in Figure 2. The sampling areas of bare land, alfalfa-covered land, and wheat-covered land were $41,000 \text{ m}^2$, $54,000 \text{ m}^2$, and $33,400 \text{ m}^2$ respectively. There were 60 sampling points on the bare land, 60 sampling points on the wheat-covered land, and 60 sampling points on the alfalfa-covered land, resulting in a total of 180 sampling points. The data were collected from May 2020 to July 2021, and the

sampling depth was in the range of 0–20 cm. A UAV was used to acquire multispectral remote sensing images. The topsoil samples were collected near the crop roots; a 20-cm deep soil tank was drilled by a soil drill; the trim pipe was taken out and zeroed, and then placed in the soil tank for reading. The data were repeatedly measured three times, and the average measurement value was denoted as a soil conductivity of a specific sampling point. During the data sampling process, the GPS was used to record the position of each sampling point.

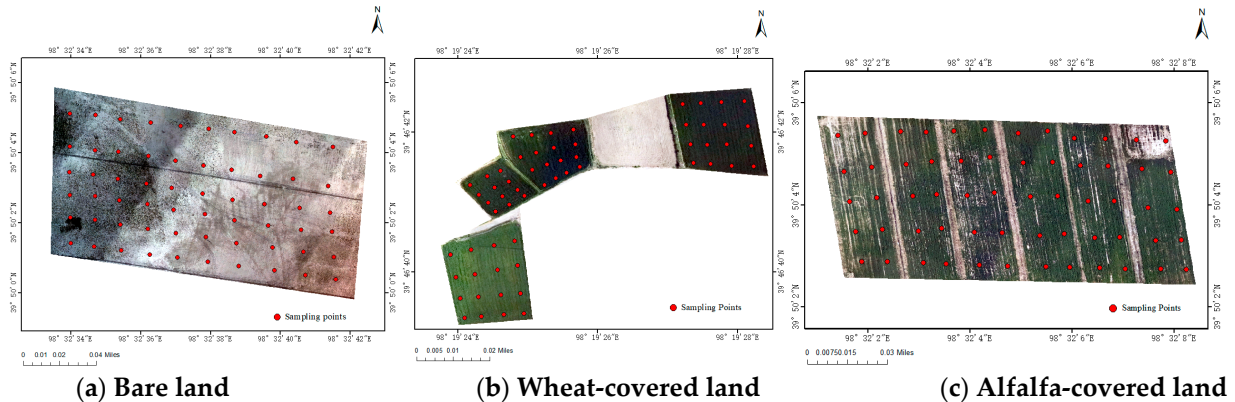


Figure 2. The sampling area.

2.3. Salinity Index Construction

The spectral index is obtained by combining the spectral reflectance of each band according to the spectral characteristics of the ground feature. The spectral index is a simple, effective, and empirical measurement of the distribution of surface features. It has been widely used in global and regional land cover, vegetation classification and environmental changes, primary productivity analysis, crop and pasture yield estimation, and drought monitoring [33–35]. In this study, the soil spectral index is used as a remote sensing evaluation index, and the salinity index is calculated by the extracted spectral reflectance. In addition, the red edge band is introduced, and 16 salinity indexes and 16 vegetation indexes are selected, as shown in Tables 2 and 3.

Table 2. The calculation formulae of the salinity indexes.

Spectral Index	Calculation Formula	Reference
Normalized Difference Soil Index (NDSI)	$NDSI = (R - NIR) / (R + NIR)$	Khan [36]
Normalized Difference Soil Index-reg (NDSI-reg)	$NDSI-reg = (RedEdge - NIR) / (RedEdge + NIR)$	Zhang [37]
Salinity index (S1)	$S1 = B/R$	Abbas [38]
Salinity index (S2)	$S2 = (B - R) / (B + R)$	
Salinity index (S3)	$S3 = (G \times R) / B$	
Salinity index (S4)	$S4 = \sqrt{B \times R}$	
Salinity index (S5)	$S5 = (B \times R) / G$	
Salinity index (S6)	$S6 = (R \times NIR) / G$	
Brightness index (BI)	$BI = \sqrt{R^2 + NIR^2}$	Khan [36]
Salinity index1 (SI1)	$SI1 = \sqrt{G \times R}$	Douaoui [21]
Salinity index1-reg (SI1-reg)	$SI1-reg = \sqrt{G \times RedEdge}$	Zhang [37]
Salinity index2 (SI2)	$SI2 = \sqrt{G^2 + R^2 + NIR^2}$	Douaoui [21]
Salinity index2-reg (SI2-reg)	$SI2-reg = \sqrt{G^2 + RedEdge^2 + NIR^2}$	Zhang [37]
Salinity index3 (SI3)	$SI3 = \sqrt{G^2 + R^2}$	Douaoui [21]
Salinity index3-reg (SI3-reg)	$SI3-reg = \sqrt{G^2 + RedEdge^2}$	Zhang [37]
Soil Index-T (SI-T)	$SI-T = 100(R - NIR)$	

Note: *B*, *G*, *R*, *NIR*, and *RedEdge* denote the spectral reflectance values at the wavelengths of 450 nm, 560 nm, 650 nm, 840 nm, and 730 nm, respectively.

Table 3. The calculation formulae of the vegetation indexes.

Spectral Index	Calculation Formula	Reference
Normalized Difference Vegetation Index (NDVI)	$NDVI = (NIR - R) / (NIR + R)$	Khan [36]
Normalized Difference Vegetation Index-reg (NDVI-reg)	$NVSI-reg = (NIR - RedEdge) / (NIR + RedEdge)$	
Difference Vegetation Index (DVI)	$DVI = NIR - R$	Zhang [37]
Difference Vegetation Index-reg (DVI-reg)	$DVI-reg = NIR - RedEdge$	
Enhanced Vegetation Index (EVI)	$EVI = 2.5(NIR - R) / (NIR + 6R - 7.5B + 1)$	Liu [39]
Enhanced Vegetation Index-reg (EVI-reg)	$EVI-reg = 2.5(NIR - RedEdge) / (NIR + 6 RedEdge - 7.5B + 1)$	Zhang [37]
Triangle Vegetation Index (TVI)	$TVI = 0.5[120(NIR - G) - 200(R - G)]$	Zhang [37]
Soil Regulation Vegetation Index (SRVI)	$SRVI = (1 + L)(NIR - R) / (NIR + R + L)$	Zhang [37]
Normalized Difference Greenness Index (NDGI)	$NDGI = (G - R) / (G + R)$	Albed [2]
Normalized Difference Soil Index (NDSI)	$NDSI = (R - NIR) / (R + NIR)$	Khan [36]
Normalized Difference Soil Index-reg (NDSI-reg)	$NDSI-reg = (RedEdge - NIR) / (RedEdge + NIR)$	Zhang [37]
Simple Ratio Index (SR)	$SR = NIR/R$	Birth [40]
Chlorophyll Vegetation Index (CVI)	$CVI = (NIR/G)(R/G)$	
Modified Chlorophyll Absorption Ratio Index (MCARI)	$MCARI = [RedEdge - R - 0.2(RedEdge - G)] \times RedEdge/R$	
Optimized Soil-Adjusted Vegetation Index (OSAVI)	$OSAVI = (1 + L)(NIR - R) / (NIR + R + L)$	Zhang [37]
Red Edge Chlorophyll Index (CI-reg)	$CI-reg = RedEdge/R - 1$	

Note: B, G, R, NIR, and RedEdge denote the spectral reflectance values at the wavelengths of 450 nm, 560 nm, 650 nm, 840 nm, and 730 nm, respectively.

2.4. Model Construction and Accuracy Evaluation

Using the soil spectral index values measured by the UAV multispectral sensor and the measured data of the soil salt content as the input and output data of the model, respectively, the support vector machine regression (SVR), backpropagation neural network (BPNN), random forest (RF), and extreme learning machine (ELM) were used to establish the soil salt content inversion model. The logistic function was selected as a kernel function of the SVR, and BPNN, RF, and ELM were realized by MATLAB R2016a software.

Model accuracy was conducted using the determination coefficient (R^2), root mean square error (RMSE), and performance deviation ratio (RPD). The larger the value of R^2 was, the lower the RMSE value was, and the better the model effect was. The RPD was divided into three levels denoted as class A ($RPD > 2.0$), class B ($1.40 \leq RPD \leq 2.0$), and class C ($RPD < 1.40$) [4,34]. The calculation formulae of the evaluation indexes are as follows:

$$R^2 = \frac{\sum_{i=1}^n (\hat{y}_i - \bar{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y}_i)^2} \quad (1)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (\hat{y}_i - y_i)^2}{n}} \quad (2)$$

$$RPD = \frac{\sqrt{\frac{\sum_{i=1}^n \bar{V}(y_i)^2}{n}}}{RMSE} \quad (3)$$

where $\hat{y}_i$, y_i , and $\bar{y}_i$ denote the predicted, measured, and average measured values of soil salt content, respectively; n is the number of samples.

3. Results and Discussion

3.1. Statistical Analysis of Soil Salinity

The 60 measured soil salt content samples were divided into five groups, namely, non-saline soil, mild-salinization soil, moderate-salinization soil, severe-salinization soil, and saline soil. Randomly select 40 samples as the training set and the other 20 as the test set. The classical statistical method is used to calculate the soil salt content, and the sample distribution is shown in Table 4. On the bare land, the proportion of non-saline soil is 5%. Alfalfa-covered land and wheat-covered land are cultivated land, and the soil salinity is

lower than the bare land; therefore, on alfalfa-covered land, the proportion of non-saline soil is 18.3%, and in wheat-covered land, the proportion of non-salt soil is 26.7%.

Table 4. The statistical analysis of soil salinity.

Sample		Number of Samples						Salt Content(ds/m)			
		Non-Saline Soil		Light Saline Soil	Moderately Saline Soil	Heavy Saline Soil	Saline Soil	Maximum	Minimum	Average	Standard Deviation
Bare land	Total sample	60	3	9	10	12	26	4.89	1.30	3.51	0.536
	Training set	40	2	5	7	14	17	4.89	1.30	3.62	0.541
	Test set	20	1	4	3	8	9	4.63	2.57	3.45	0.520
Alfalfa-covered land	Total sample	60	11	15	13	12	9	2.68	1.22	1.59	0.322
	Training set	40	7	11	8	9	6	2.68	1.36	1.65	0.339
	Test set	20	4	4	5	3	3	2.01	1.22	1.47	0.252
wheat-covered land	Total sample	60	16	23	11	6	4	2.76	1.11	1.34	0.282
	Training set	40	11	16	8	4	3	2.76	1.17	1.39	0.289
	Test set	20	5	7	3	2	1	1.33	1.11	1.29	0.258

3.2. Correlation Analysis between Spectral Index and Soil Salt Content

Sixteen calculated salinity indexes, 16 vegetation indexes, and soil salt content were analyzed, and obtained results are shown in Tables 5 and 6.

Table 5. The correlation between the soil salt index of the bare land and the soil salt content.

Salinity Index	Correlation Coefficient	Salinity Index	Correlation Coefficient
	Bare Land		Bare Land
NDSI	0.522 **	BI	0.697 **
NDSI-reg	0.343 **	SI1	0.627 **
S1	0.557 **	SI1-reg	0.611 **
S2	0.558 **	SI2	0.649 **
S3	0.693 **	SI2-reg	0.605 **
S4	0.735 **	SI3	0.626 **
S5	0.732 **	SI3-reg	0.615 **
S6	0.573 **	SI-T	0.397 **

** At the level of 0.01 (two tailed), the correlation was significant.

Table 6. The correlation between the vegetation index and the soil salt content for the alfalfa- and wheat-covered lands.

Vegetation Index	Correlation Coefficient		Vegetation Index	Correlation Coefficient	
	Alfalfa-Covered Land	Wheat-Covered Land		Alfalfa-Covered Land	Wheat-Covered Land
NDVI	−0.751 **	−0.796 **	NDGI	−0.669 **	−0.314 *
NDVI-reg	−0.588 **	−0.132	NDSI	0.741 **	0.671 **
DVI	−0.508 **	0.438 **	NDSI-reg	0.585 **	0.132
DVI-reg	−0.290 *	0.405 **	SR	−0.648 **	−0.692 **
EVI	−0.066	−0.059	CVI	−0.535 **	0.039
EVI-reg	0.185	−0.246	MCARI	−0.609 **	0.354 **
TVI	−0.497 **	0.450 **	OSAVI	−0.722 **	−0.136
SRVI	−0.753 **	−0.601 **	CI-reg	−0.670 **	−0.069

** At the level of 0.01 (two-tailed), the correlation was significant; * At the level of 0.05 (two-tailed), the correlation was significant.

As shown in Table 5, 16 salt indexes of the bare land achieved significant correlation. The salt indexes of the model input layer in descending order were as follows: S4, S5, BI, S3, SI2, SI1, SI3, SI3-reg, SI1-reg, SI2-reg, S6, S2, S1, NDSI, SI-T, and NDSI-reg.

According to the results in Table 6, except for EVI and EVI-reg indexes, the remaining 14 salinity indexes of the Alfalfa-covered land achieved accurate results. The vegetation indexes of the model input layer in descending order were as follows: SRVI, NDVI, NDSI, OSAVI, CI-reg, NDGI, SR, MCARI, NDVI-reg, NDSI-reg, CVI, DVI, TVI, and DVI-reg.

Among 16 vegetation indexes in the Wheat-covered field, the vegetation indexes of the model input layer in descending order were as follows: NDVI, SRVI, SR, NDSI, TVI, DVI, DVI-reg, MCARI, and NDGI.

3.3. Optimal Soil Salt Content Machine Learning Model for Different Land Cover Types

The spectral index data with high correlation were used as input data of the model, and the corresponding soil salt content data were used as dependent data. The soil salt content model was constructed using three machine learning-based methods, namely SVR, RF, and BPNN. The results of the proposed model on the training and test sets are given in Table 7.

Table 7. The results of the soil salt content inversion model based on the spectral index.

Model	Data	Training Set		Testing Set		RPD
		R_c^2	$RMSE_c$	R_v^2	$RMSE_v$	
SVR	Bare land	0.658	0.110	0.419	0.403	1.430
	Alfalfa-covered land	0.804	0.150	0.601	0.227	1.422
	Wheat-covered land	0.831	0.037	0.717	0.032	2.600
RF	Bare land	0.560	0.374	0.571	0.357	1.502
	Alfalfa-covered land	0.768	0.163	0.440	0.343	1.439
	Wheat-covered land	0.841	0.039	0.547	0.044	1.870
BPNN	Bare land	0.449	0.323	0.647	0.309	1.734
	Alfalfa-covered land	0.790	0.260	0.840	0.399	1.809
	Wheat-covered land	0.857	0.034	0.836	0.027	2.100
ELM	Bare land Bare land	0.461	0.342	0.707	0.290	1.852
	Alfalfa-covered land	0.756	0.165	0.806	0.240	1.431
	Wheat-covered land	0.863	0.038	0.739	0.033	2.508

The predicted soil salt values of nine soil salt inversion models were compared with the measured values of soil salt in the test set. As shown in Table 7 and Figure 3, the proposed soil salt content inversion model based on the spectral index achieved a good inversion effect; most of the determination coefficient (R_c^2) values on the training set were above 0.7, the root mean square error ($RMSE_c$) was below 0.4, and the performance deviation ratio (RPD) was above 1.4, demonstrating high accuracy and good stability. However, the BPNN and ELM models performed slightly poorly on the training set for the bare land; namely, their R_c^2 values were 0.449 and 0.461, while their $RMSE_c$ values were 0.323 and 0.342, respectively. Among the constructed models, the salt inversion model established using the wheat-covered land data had the best effect, achieving R_c^2 of 0.863 and $RMSE_c$ of 0.038.

As shown in Figure 3, among the four models in the same study area, the best soil salt inversion model for the bare land was the ELM model; on the test set, its R_v^2 was 0.707, $RMSE_v$ was 0.290, and RPD was 1.852; there was no cover on the bare surface land. The best soil salinity inversion model for the alfalfa-covered land was the BPNN model; on the test set, its R_v^2 was 0.840, $RMSE_v$ was 0.399, and RPD was 1.809. The best soil salinity inversion model for the wheat field was also the BPNN model; on the test set, its R_v^2 was 0.836, $RMSE_v$ was 0.027, and RPD was 2.100. Alfalfa-covered land and wheat-covered land are both salinized land covered by vegetation, indicating that it is suitable to establish a model based on the salt index calculated from the soil spectral reflectance of the bare land. Therefore, the optimal soil salt inversion model for the bare land is the ELM model, whereas the optimal soil salt inversion model for agricultural land with a vegetation cover is the BPNN model.

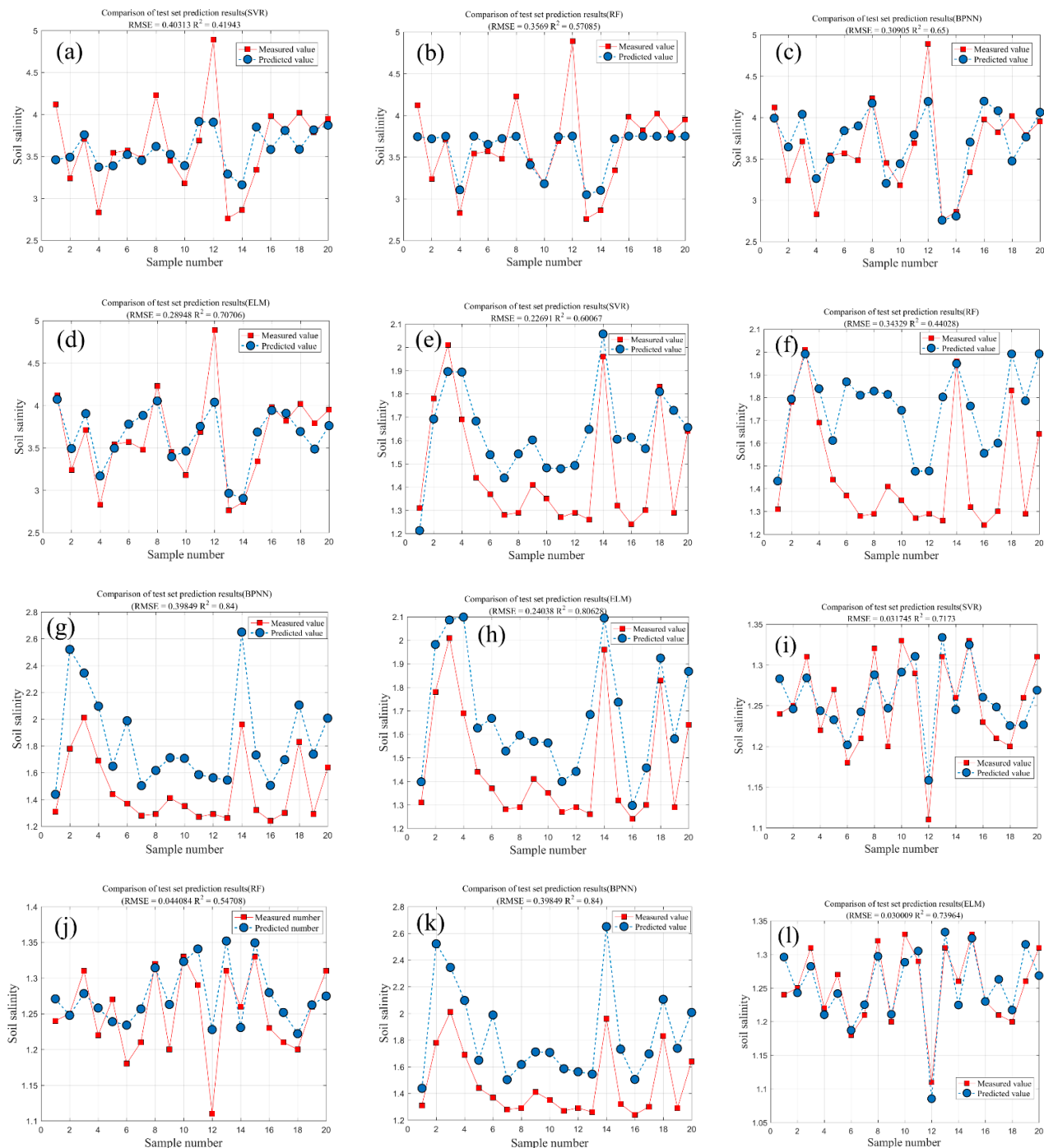


Figure 3. The proposed model prediction results. Note: (a) Bare land SVR model; (b) Bare land RF model; (c) Bare land BPNN model; (d) Bare land ELM model; (e) Alfalfa-covered land SVR model; (f) Alfalfa-covered land RF model; (g) Alfalfa-covered land BPNN model; (h) Alfalfa-covered land ELM model; (i) Wheat-covered land SVR model; (j) Wheat-covered land RF model; (k) Wheat-covered land BPNN model; (l) Wheat-covered land ELM model.

The accuracy of each of the constructed salt inversion models was evaluated for the three study areas, and the corresponding scatter diagrams were drawn. As shown in Figure 4, the R_v^2 values of all models were higher than 0.4. The highest R_v^2 value was 0.840, which indicated a good inversion effect. For the SVR model, the best modeling effect was achieved for the small- and medium-sized wheat fields in all three study areas; the RPD was 2.600. For the RF model, the best modeling effect was achieved for the bare land;

the *RPD* was 1.502. For the BPNN model, the inversion effect of the alfalfa-covered land was similar to that of the wheat fields but better than that of the bare land. For the ELM model, the inversion effects of the alfalfa-covered land and wheat fields were similar, and both better than that of the bare land; the *RPD* of the alfalfa-covered land and wheat fields were 1.431 and 2.508, respectively. Thus, the SVR and BPNNs achieved the best soil salt inversion effect in all three study areas for wheat fields, while the RF model achieved the best soil salt inversion effect for the bare land.

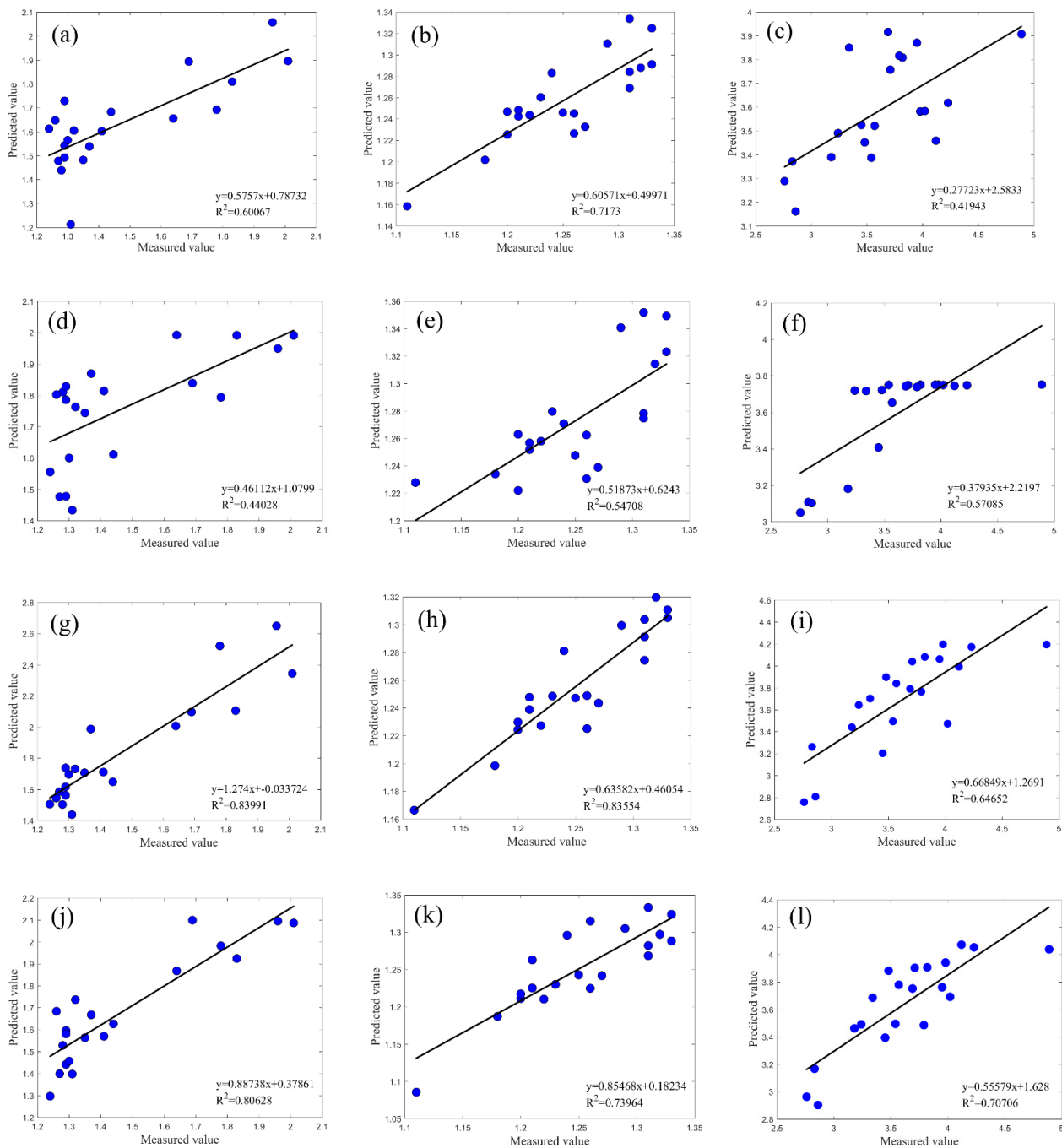


Figure 4. Scatter diagram of the measured and predicted data. Note: (a) Alfalfa-covered land SVR model; (b) Wheat-covered land SVR model; (c) Bare land SVR model; (d) Alfalfa-covered land RF model; (e) Wheat-covered land RF model; (f) Bare land RF model; (g) Alfalfa-covered land BPNN model; (h) Wheat-covered land BPNN model; (i) Bare land BPNN model; (j) Alfalfa-covered land; (k) Wheat-covered land ELM model; (l) Bare area ELM model.

4. Discussion

The UAV multispectral remote sensing has been widely used in large-scale soil salinity monitoring of saline-alkali land covered by crops, and it is the future development direction of precision agriculture [21,41,42]. Compared with other monitoring methods, it has the advantages of easy data acquisition and continuous dynamic monitoring [43]. The current research on soil salinity monitoring has been mainly focused on the direct inversion of the bare land. In this paper, using the multispectral remote sensing data of the land with different vegetation coverage, the SVR, RF, BPNN, and ELM soil salt inversion models are established. The four models have achieved good inversion results on all land types, and their *RPD* values were above grade B, demonstrating good reliability.

Therefore, by combining UAV multispectral remote sensing with the four machine learning-based models, the soil salt content data can be obtained. This combination can ensure rapid inversion of the soil salt content data of cultivated and bare land on a regional scale and provide the land salt information rapidly and accurately. Wei [43] quantitatively estimated the soil salt content using the UAV multispectral images and established the BPNN, SVR, and RF model. The results showed that the RF model had the best inversion effect on the bare land. Similarly, among the RF models established in this study, the model performed the best in soil salt inversion on the bare land, R_v^2 and *RPD* reached 0.571 and 1.502. Relatively good inversion results were achieved for the wheat fields and alfalfa-covered land, showing that the RF model is more suitable for estimating soil salt in bare land areas without vegetation cover [26]. The comparison of the 4 established machine learning-based models in the same research area has indicated that the ELM model is the most suitable for soil salt inversion in bare land without any vegetation cover. The test set R_v^2 reached 0.707, and *RPD* was 1.852. For saline cultivated land with vegetation cover, the BPNN model can provide a better inversion effect than the other three machine learning-based models. The R_v^2 and *RPD* of the test set were above 0.830 and 1.800.

Many studies have shown that the red edge band has a significant correlation with the spectral characteristics of vegetation canopy and is more sensitive to soil salt, which improves the accuracy of soil salt inversion [29,37,44]. Hu [45] used a UAV to collect remote sensing images of the bare land and vegetation coverage area for modeling and prediction. The best prediction effect was achieved for the area with vegetation coverage. Thus, the spectral index calculated by introducing the red edge band improves soil salt inversion accuracy of saline cultivated land with vegetation cover. In the SVR, BPNN, and ELM models constructed in the three research areas of this study, the modeling effects of the saline cultivated land covered with alfalfa and wheat are better than that for the bare land. The reason is that the red edge band is introduced in calculating the spectral index of saline-alkali land. Therefore, the red edge band is also introduced in the inversion of the soil salt content of the bare land. The accuracy of the salt inversion model is not high for the bare land, indicating that the red edge band is mainly for the inversion of soil salinity in cultivated land covered by vegetation. In general, an optimal machine learning-based inversion model combined with the red edge band can provide higher accuracy in soil salt inversion and monitoring on the regional scale of the Taolai River in the Hexi corridor.

There are many types of crops on the Bian Wan farm in an irrigation area. Allbed [46] confirmed the potential long-term link between the soil salinity changes and crop cover type. The UAV multispectral remote sensing with the red edge band can quickly and effectively retrieve the soil salt content data of land with different crop cover and can realize quantitative evaluation and monitoring of saline soil at a regional farm scale. However, there can be significant differences in the distribution law of soil salt content between irrigation systems and season, which will be further studied in the future. This study analyzes the convenience and advantages of using UAV and combining it with machine learning-based models in the field of soil salinity monitoring and determines an optimal inversion model for two crop coverage. This study also forms a rapid soil salt content big data platform combined with satellite remote sensing upscaling data in the irrigation area, realizes the long-term high-precision monitoring of soil salinity in the farm area,

provides a theoretical basis for quantitative evaluation of saline cultivated land crops and determination of saline-alkali land irrigation system, and finally, gives technical guidance for saline-alkali land treatment, construction, and development of ecological agriculture.

5. Conclusions

This study analyzed the rapid monitoring and inversion of cultivated land soil salinization under different vegetation cover using UAV multispectral inversion. The saline-alkali land with three different covers in the arid region of Northwest China was used as a research object. Combining the multispectral remote sensing data collected by a UAV and four machine learning-based methods, a soil salt inversion model was constructed. By comparing the accuracy of the constructed models for different land cover types, the optimal inversion model was determined for each of the considered cover types.

The results presented in this study indicate that it is suitable to establish an inversion model using the salt index data obtained from the soil spectral reflectance of the bare land. The best model for retrieving the soil salt content for the bare land was the ELM model, and on the test dataset, it achieved R^2 of 0.707, $RMSE_v$ of 0.290, and RPD of 1.852. For the agricultural land with vegetation cover, the best model for soil salinity inversion using the vegetation index is the BPNN model; on the test dataset, it achieves R^2 of 0.836, $RMSE_v$ of 0.027, and RPD of 2.100. The ELM model can quickly and accurately reflect the soil salt of the bare land, and the BPNN model can effectively reflect the soil salt of cultivated land covered with vegetation.

The four models constructed in this study have achieved good soil salt inversion results in all three study areas. The introduction of the red edge band could effectively improve the soil salt inversion accuracy of the saline-alkali land with vegetation cover. The SVR and BPNN models achieved the best soil salt inversion effect in the three study areas for the wheat-covered land, while the RF model achieved the best soil salt inversion effect for the bare land. In general, an optimal machine learning-based inversion model combined with the red edge band can provide higher accuracy in soil salt inversion and monitoring on the regional scale of the Taolai River in the Hexi corridor.

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