Nature Environment and Pollution Technology
An International Quarterly Scientific Journal

p-ISSN: 0972-6268 e-ISSN: 2395-3454	Vol. 16	No. 1	pp. 141-146	2017

Original Research Paper | Open Access

Estimating Soil Salt Content in the Keriya Oasis Using Hyperspectral Slope Index

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Nat. Env. & Poll. Tech.
Website: www.neptjournal.com

Received: 13-02-2016
Accepted: 02-05-2016

Key Words:
Soil salt content
Spectral slope
Hyperspectral reflectance
Keriya Oasis

ABSTRACT

Hyperspectral data provide valuable information for salt content estimation. In this paper, soil samples were collected from the Keriya Oasis, Southern Xinjiang, China. Samples were bagged, brought to the laboratory, air-dried, ground, and sieved using 2 mm size sieve. Soil salt contents were measured and the reflectance spectra were collected using FieldSpec3 in laboratory condition. The continuum removal (CR) reflectance was obtained after smoothing and averaged spectral data conversion of 10 nm interval. A total of 8 spectral slopes at the wavelength between 365-375 nm, 1435-1465 nm, 1855-1865 nm, 1915-1925 nm, 2085-2095 nm, 2295-2315 nm, 2365-2395 nm and 2465-2475 nm were calculated based on the correlation analysis between soil salt content and its spectrum. Thirty of 40 samples were used for establishing hyperspectral model for estimating soil salt content and the other 10 samples were for the model verification. The multiple linear regression (MLR) and partial least squares regression (PLSR) were used to model and estimate soil salt content. The results showed that, when soil salt content is higher than 2.10 $g \cdot kg^{-1}$, spectral slope values increase with the increase of salt content. The estimation accuracy of the model based on MLR was higher than the model based on PLSR. The R^2 for calibration and validation of the optimum multiple linear regression model were up to 0.834 and 0.664, respectively, and its RMSE values of calibration and validation were 2.9707 and 3.2691, and the RPD value was 2.09, respectively. This spectral slope based model was a supplementary modelling for hyperspectral soil salinity estimation, and can be a basis for future satellite-based hyperspectral monitoring and evaluation of soil salinity.

INTRODUCTION

Soil salinization is a widespread land degradation problem with severe environmental, social and economic consequences. Generally it occurs in the arid and semi-arid areas, especially in the areas where parent material is rich in soluble salts and high groundwater level (Amezketa 2006). In the oasis agricultural areas of northwestern China, due to the special geographic conditions and overexploitation of land and water resources, soil salinization has become a major constraint not only for the sustainable development of regional agriculture, but also for the national food and ecological security (Abliz et al. 2016). Therefore, timely and effective monitoring and accurate assessment on the extent and severity of soil salinity has become a priority for the regional ecological and socioeconomic sustainability (Sidike et al. 2014).

Soil salt content could be reflected in the spectral behaviour of soil electromagnetic spectrum, and the severity of salinization can also quantified by analysing the reflection and absorption characteristics at the specific wavelengths. Remote sensing has been widely used in the monitoring of soil salinization for the last two decades (Farifteh et al. 2006). Fine spectral resolution and rich spectral information of the satellite- or field-measured hyperspectral data provides new means for the spectroscopic information extraction of the saline soils. In recent years, the soil hyperspectral data are not only used to estimate soil organic matter and heavy metal content (Hou et al. 2014, Song et al. 2015), and also applied in the quantitative modelling of soil salinity (Nawar et al. 2015, Wang et al. 2012, Bilgili et al 2011). Zhao et al. (2014) statistically analysed the relationships between the spectral reflectance and the soil electrical conductivity and pH value, and established a regression model for soil salinity estimation. Peng et al. (2014) developed an inversion model for quantifying the salt content using hyperspectral soil spectra, measured salt content and conductivity. According to the research by Xu & Huang (2014), the processed soil spectra by logarithmic and first-order differential treatment found effective for establishing the inversion model using the partial least squares regression. Currently, the widely used statistical modeling methods on soil salinity estimation using spectral reflectance mainly include the principle component analysis (PCA), multiple linear regression (MLR) and partial least squares regression (PLSR), and the inversion models have been gradually combined with hyperspectral satellite data for the remotely sensed monitoring of soil salinization in large scales (Csillag 1993, Huang et al. 2015, Zhang et al. 2011). However, more information retrieval models need to be explored based on the statistical correlation analysis between salt content and soil spectra obtained from near and remote sensors.

In this paper, the Keriya Oasis in the Xinjiang Uyghur Autonomous Region, China, was selected as our research area. Soil samples were collected and brought to the laboratory for chemical analysis and spectrum collection. The relationships between soil salt content and spectral reflectance were analysed after spectral preprocessing, and then spectral slope values were calculated for the featured wavelengths. Soil salinity estimation models were developed and validated using partial least squares regression and measured salt content. Results from this paper will be a complementary for the hyperspectral model estimation of soil salinity, and thus provide basis for the future hyperspectral satellite remote sensing monitoring and evaluation of soil salinization.

MATERIALS AND METHODS

Study site: The Keriya Oasis (36°45'~37°15'N 81°10' ~81°45'E) is located in the southern edge of the Taklimakan Desert and the mid-northern foot of the Kunlun Mountains, administratively lies in the territory of Keriya County (Nurmemet et al. 2015). This region has a temperate continental arid climate characterized by hyper aridity with an average of about 45 mm annual precipitation and mean evaporation amount of 2600 mm which is more than 50 times the mean annual precipitation (Ghulam et al. 2004). The oasis is situated on a fluvial plain with relatively flat terrain, loose soil, high salt concentrations and lack of soil fertility (Gong et al. 2015, Sawut et al. 2014). Oasis agriculture is the main land-use type, which relies on the water resources from the Keriya River for irrigation. Hyper-arid climate, topographic condition and shallow groundwater level brought dissolved salts to the land surface, causing soil salinization and desertification, especially in the transitional belt between oasis and desert, and therefore severely restricting the sustainable development of oasis agriculture.

Soil sampling and laboratory analysis: A total of 40 sites were chosen for soil sampling based on the visual determination on land cover conditions and salinity degrees. Soil samples were collected from the soil surfaces (0-10 cm), bagged and brought to the laboratory. Samples were air dried, ground and sieved through a 2 mm mesh, and then split into two groups, one for chemical analysis and the other one for spectral measurement. Soil parameters including soil salt content, electrical conductivity and pH value, were determined by preparing soil solution with soil-water ratio of 1:5. The pH value was determined using LP115 pH meter, and the salt content and electrical conductivity ($EC_{1:5}$) of the solution were measured using Orion 115A +. The maximum salt content of the samples was 19.60 $g \cdot kg^{-1}$, the minimum content was 2.10 $g \cdot kg^{-1}$, and the average content for the whole samples was 9.29 $g \cdot kg^{-1}$. Besides, the pH values were ranged from 7.90 to 9.88 (mildly alkaline).

Spectral measurement: The FieldSpec3 portable field spectrometer (Analytical Spectral Device, ASD, USA) was used for soil spectra collection. Spectra were measured in a dark room, and each soil sample was measured five times repeatedly. In total, 200 groups of soil spectral reflectance data were obtained at the wavelengths range of 350-2500 nm, and then the average spectra were calculated for each soil samples.

Spectral data preprocessing and slope calculation: To remove the spectral noise and to ensure accuracy of the estimation models, different pretreatments were applied to the raw spectral data. The continuum removal (CR) reflectance was calculated after smoothing and converting spectral data to averaged value of 10 nm interval (Kemper & Stefan 2002). The ViewSpecPro software was used for continuum removal to emphasize the spectral absorption differences and highlight the absorption features from the baseline (Noomen et al. 2006).

In this slope algorithm, CR reflectance values from two adjacent featured spectral wavelengths were used for slope calculation, the difference between reflectance values divided by the difference between the corresponding wavelengths (Lugassi et al. 2014), which was calculated as follows:

$$slope = \frac{r_2 - r_1}{x_2 - x_1} \qquad ...(1)$$

Where, x is the wavelength; r is CR reflectance.

Modelling and validation: Eight pair of CR reflectance for corresponding featured slope was chosen and used for modelling. MLR and PLSR were used for constructing the soil salinity prediction model. Randomly selected spectra of 30 samples and the measured soil salinity data were used for modeling, the remaining 10 used to validate the model. The performance and validity of the models were assessed using the coefficient of determination (R^2), root mean square error

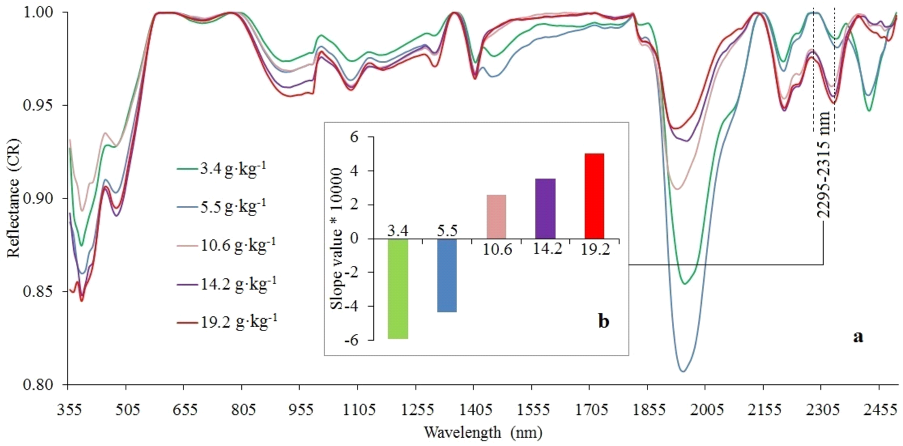

Fig. 1 (a) Continuum removal (CR) reflectance spectra of soil samples with different salt content; (b) Slope tendency on the 2295-2315 nm spectral range for demonstrating the slope changes with changes in soil salt content.

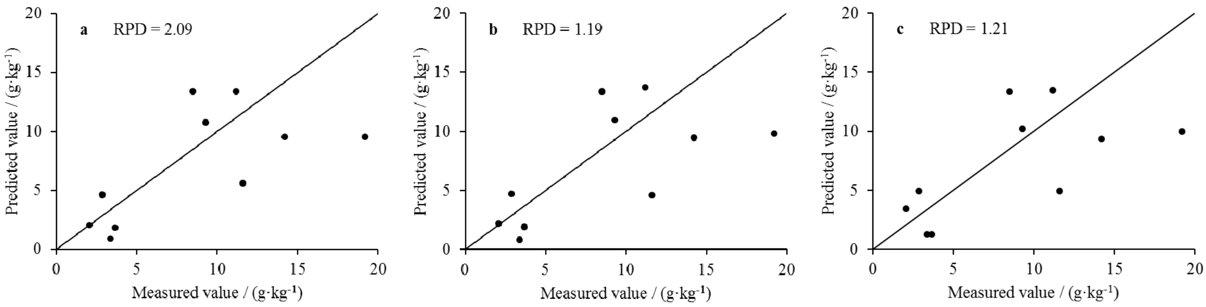

Fig. 2: Comparison of the measured and prediction soil salt content by MLR model. a is the validation result for M_1; b for the M_2 and c for M_3.

(RMSE) and the residual predictive deviation (RPD), which were calculated as shown below:

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(Y_i - \hat{Y}_i)^2}{\sum_{i=1}^{N}(Y_i - \bar{Y})^2} \quad ...(2)$$

$$RMSE = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2} \quad ...(3)$$

$$RPD = \frac{SD_s}{RMSE_p} \quad ...(4)$$

Where, n is the sample size; Y_i is the measured salt content of soil samples; $\hat{Y}_i$ is the estimated salt content of soil samples by the model; $\bar{Y}$ is the average salt content of soil samples; SD_s is the standard deviation of measured salt content; $RMSE_p$ is the root mean square error of the predicted salt content.

Statistically, the goodness of the model prediction reflected by R^2, and the RMSE indicates the precision of the model estimation. The model prediction accuracy is higher when R^2 is higher and the RMSE value is lower; conversely, accuracy is lower. PRD value represents the correlation between measured and predicted values. When RPD> 2, the model estimation accuracy is excellent; when 1.4 <RPD <2:00, the accuracy is acceptable; when RPD <1.4, indicates poor accuracy (Rossel et al. 2006). When evaluating the overall model accuracy, model results with greater PRD and R^2 values and lower RMSE should be chose as the optimal estimation model.

RESULTS AND DISCUSSION

Spectral slope analysis: The wavelength ranges for featured slopes were selected by observing and analysing the spectral response of CR reflectance to different salt contents. A total of 8 spectral slopes at the wavelength between 365-375 nm, 1435-1465 nm, 1855-1865 nm, 1915-1925 nm, 2085-2095 nm, 2295-2315 nm, 2365-2395 nm and 2465-2475 nm were calculated based on the correlation analysis between soil salt content and CR reflectance spec-

Table 1: Multiple linear regression (MLR) model results of the correlations between different slope values and soil salt content.

Model	Calibration		Validation		
	R^2	RMSE	R^2	RMSE	RPD
M_1= 47.68-22626s_1+50648s_2+4291s_3-15751s_4+5601s_5-31472s_6-84356s_7-360s_8	0.834	2.9707	0.664	3.2691	2.09
M_2= 46.93-19309s_1+51409s_2+5555s_3-15285s_4+6181s_5-31663s_6-80527s_7	0.832	2.7615	0.647	4.7606	1.19
M_3= 50.90-24730s_1+52110s_2-16234s_4+7380s_5-33108s_6-85582s_7	0.819	2.6822	0.646	4.6866	1.21

Note: M_i represents the estimated value of soil salt content (g·kg^{-1}); s_j represents the selected slope values at the wavelengths between 365-375 nm, 1435-1465 nm, 1855-1865 nm, 1915-1925 nm, 2085-2095 nm, 2295-2315 nm, 2365-2395 nm and 2465-2475 nm

Table 2: Partial least squares regression (PLSR) model results of the correlations between different slope values and soil salt content.

Model	Calibration		Validation		
	R^2	RMSE	R^2	RMSE	RPD
M_4= 45.53-15454s_1+51393s_2+6438s_3-15114s_4+6695s_5-31319s_6-75480s_7-92s_8	0.830	2.7785	0.620	4.9298	1.14
M_5= 37.72+47366s_2+10356s_3-14886s_4+5924s_5-22957s_6-50079s_7	0.792	2.8772	0.593	5.1248	1.10

tra (Fig. 1a). The changes in slope response to salt contents were also analysed. For example, at the wavelength range of 2295-2315 nm, slope values increase with the increase of soil salt contents (Fig. 1b).

MLR analysis: Featured slopes were calculated based on the CR reflectance and corresponding wavelength using DPS data processing software. MLR models were developed at the significant level of 0.05 using SPSS 20.0 software. The regression models and its calibration and validation results are given in Table 1. Statistical results showed that, the accuracy of calibration and validation of the model M_1 was higher than the other two models. The calibrated R^2 of the M_1 reached to 0.834 and RMSE was 2.297, its validation R^2, RMSE and RPD values were 0.664, 3.269 and 2.09, respectively, indicating that the model M_1 has a high fitting accuracy and acceptable stability for salt content estimation. The remaining two models, M_2 and M_3, have higher validation errors, the RPD were 1.19 and 1.21, respectively, indicating that prediction accuracies were very poor.

The correlations between soil salt content estimated by these MLR models (M_1, M_2 and M_3) and measured salt contents were analysed and compared (Fig. 2). All three model results were deviated from the 1:1 line, illustrating a lower estimate of the accuracy. Wherein the fitting degree of the three model results, M_1 has a relatively higher fitting accuracy, clarifying that the use of multiple features slopes (8) could improve the estimation accuracy of the model.

PLSR analysis: For PLSR modelling, we used the measured soil salt contents as the dependent variable, and the corresponding spectral slope value as the independent variable. Variables were analysed and PLSR model was built using SIMCA-P 11.5 software. The regression model and its calibration and validation results are given in Table 2. Statistical results showed that, the accuracy of calibration and validation of the model M_4 was better than M_5. The calibrated R^2 of the M_4 reached to 0.830 and RMSE was 2.779, its validated R^2, RMSE and RPD values were 0.620, 4.930 and 1.14, respectively, indicating that the model M_4 has an acceptable fitting precision, but less stable in salt content estimation. M_5 has a higher validation error and the RPD value was 1.10, indicating poor prediction accuracy.

Fig. 3 shows comparison of the measured and predicted soil salt content by PLSR model. d is the validation result for M_4; e is the validation result for M_5.

CONCLUSION

In this paper, MLR and PLSR were used to model and estimate soil salt content using field hyperspectral spectroscopy data collected in the Keriya Oasis of Xinjiang Uyghur Autonomous Region of China. The CR reflectance was obtained after smoothing and averaged spectral data conversion of 10 nm intervals. A total of 8 spectral slopes at the wavelength between 365-375 nm, 1435-1465 nm, 1855-1865 nm, 1915-1925 nm, 2085-2095 nm, 2295-2315 nm, 2365-2395 nm and 2465-2475 nm were calculated based on the correlation analysis between soil salt content and its spectrum.

The results show that, when soil salt content is higher than 2.10 g·kg^{-1}, spectral slope values increase with increasing salt content. The estimation accuracy of the model based

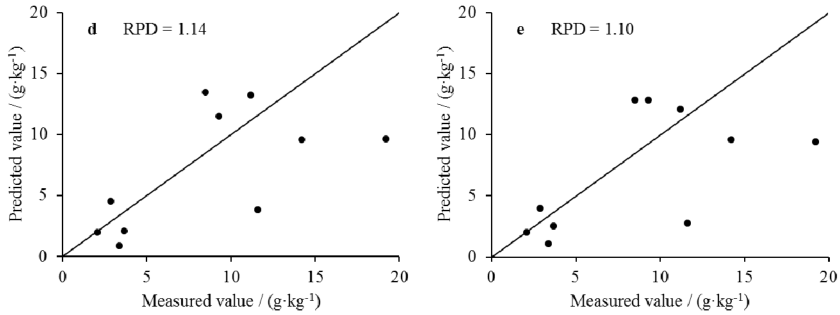

Fig. 3: The correlations analysis between soil salt content estimated by PLSR models (M_4 and M_5) and measured salt contents. Model results were deviated from the 1:1 line, illustrating a lower estimate of the accuracy. Wherein, M_4 has a relatively higher fitting accuracy than M_5.

on MLR was higher than the model based on PLSR. The R^2 values for calibration and validation of the optimum multiple linear regression model were up to 0.834 and 0.664, respectively, and its RMSE values of calibration and validation were 2.9707 and 3.2691, and the RPD value was 2.09, respectively, and thus can be used to estimate soil salt content.

Generally, soil spectral reflectance is influenced by many factors, such as soil components, particle size, surface roughness and soil moisture content. However, spectral data used in this study was measured in the laboratory, and thus the impact of soil particle size, moisture and roughness were not considered. Nevertheless, quantitative analysis on the influences of different factors on soil spectral reflectance is crucial for developing more accurate inversion models for salt content estimation.

ACKNOWLEDGEMENTS

The research was supported by the National Natural Science Foundation of China (NSFC, U1138303, 41561089, 41361016) and the special funds of Key Laboratory of Xinjiang Uyghur Autonomous Region (2014KL005).

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