SOIL ORGANIC MATTER CONTENT RETRIEVAL FROM HYPERSPECTRAL REMOTE SENSING IN WESTERN JILIN, CHINA

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1. INTRODUCTION

The analysis and forecast of the distribution and dynamics of soil organic matter (SOM) content is an essential requirement for sustainable land management, especially in Western Jilin, where the saline-alkalized land increased at a very fast rate per year and is in desperate need of improving soil. Compared to conventional analytical methods, hyperspectral remote sensing is faster, cheaper, non-destructive and has the potential to analyze various soil properties simultaneously, such as soil carbon, soil organic matter, and various other soil properties [1]. A number of linear and nonlinear models have been developed for determining the soil properties on soil spectra with different accuracy [2]. In this study, more interest was laid in detecting the sensitive bands position of SOM and a particular algorithm spectroscopists had been using was introduced and adapted to remote sensing spectral analysis successfully. Finally, a simple stepwise multiple linear regression analysis was used to produce the prediction model.

2. MATERIALS AND METHODOLOGY

The study was conducted in the west of Jilin province in China, Soil samples were collected in October 2006. Field sampling consisted of 33 sites in the study area. Basic sample preparation consisted of air-drying, ball-milling and sieving using a 2-mm mesh, soil organic matter content was determined in classic physicochemical methods of analysis, and is reported in percentage. The soil samples were scanned using the spectrophotometer ASD FieldSpec FR, the instrument measures reflectance in the wavelength range of 350-2500 nm, at 1-nm intervals. The soil samples were scanned five times on artificial light, with replicates collected at angels of 90°. An average spectral curve was calculated for each sample (from the five scans) and further used for transformations and chemometric modeling.

To reduce random noise, a mean filter smoothing was applied as a standard preparation of the soil reflectance curves before other pre-processing transformations were performed [3]. The mean filter simply takes the mean spectral value of all points within the specified window as the new value of the middle point of the window in Eq. (1)

$$\hat{R}(\lambda_j) = \frac{\sum R(\lambda_i)}{n} \qquad (1)$$

Where *i, j* is the band number, $R(\lambda_i)$ is the observed reflectance at the wavelength of λ_i, n is the size of the filter window, in this study, n was taken as 9.

For the sake of extracting useful spectral features for analyzing SOM content, a derivative computation algorithm for detecting the absorption band positions was executed on the smoothed spectra. Finite approximation can be used to estimate derivatives by suitable difference schemes in accordance with a finite band resolution, $\triangle\lambda$. The nth derivative can be estimated by Eq. (2) [3].

$$\left.\frac{d^n R}{d\lambda^n}\right|_i = \frac{\sum_{i}^{i+n} C_k R(\lambda_k)}{(\Delta\lambda)^n} \qquad (2)$$

Where $j=(2i+n)/2$, if $(2i+n)$ is even, or $j=(2i+n+1)/2$, if $(2i+n)$ is odd; The coefficients C_k are calculated using an iteration scheme.

The stepwise multiple linear regression uses a combination of the forward and backward selection techniques, in which the variables are added and removed according to a tolerance significance level, based on F probability, which was set to 0.05. Stepwise multiple linear regression is implemented in SPSS 17.0.

3. RESULTS AND DISCUSSIONS

As there is always a trade-off between noise removal and feature extraction with finite approximation, selecting a sampling interval suitable to the scale of the spectral features of interest will usually enhance the desired spectral features. In this study, the second-order derivative is computed to extract the distinguishing features with a band separation of 50nm.

Fig. 1 shows the original spectra of the soil samples while Fig. 2 is second-order derivatives of the smoothed spectra at a band separation of 50nm. As shown in Fig. 1 and Fig. 2, although the original spectra differ in magnitude between 800nm and 1300nm, they have almost identical values of the second order derivative over the same wavelength range. Several interesting spectral features are apparent in the derivative spectra that are obscure in the original spectra. For example，at about 650nm in Fig. 2，the second derivatives divided into several groups, indicating that the original spectra at these wavelengths had different ranges of curvature and there were distinguishing features. The group had second derivatives that are close to zero, corresponding to spectra that were nearly flat at these wavelengths; The group had second derivatives with more negative values, indicating that the original spectra had a concave down shape.

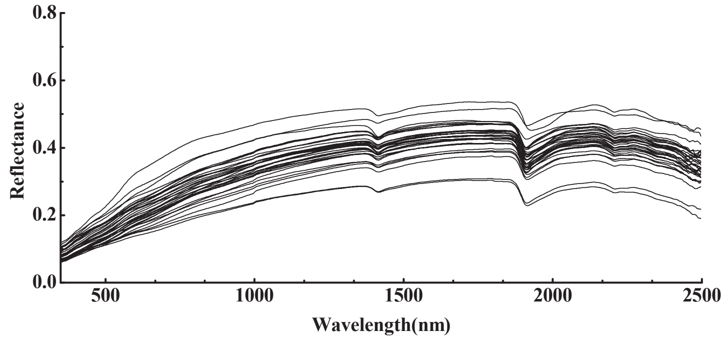

Fig.1 Original spectra of soil samples

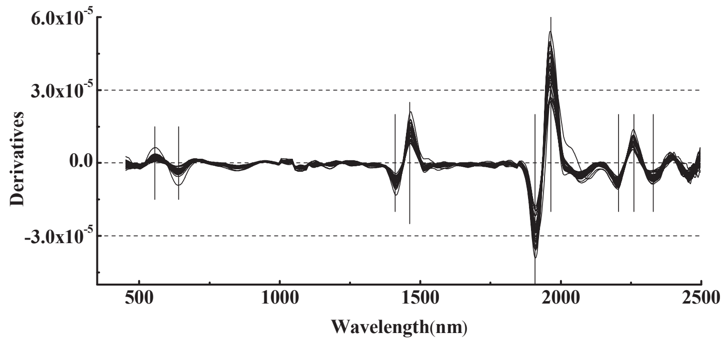

Fig.2 Second-order derivative of the smoothed spectra at a sampling intervals of 50nm

The result of the derivative analysis was that reflectance values of 9 wavebands were committed to the following analysis. They were located around wavelengths: 571, 650, 1421, 1472, 1915, 1967, 2206, 2265 and 2329nm.

The whole dataset was split randomly into 23 samples for calibration and 10 samples for validation. A stepwise multiple linear regression model was established as：

$$SOM = 4.025 - 729631.913R''_{2329} - 749600.360R''_{1421} - 309227.472R''_{1472} \qquad (3)$$

Where: R''_w is the second order derivative of reflectance at wavelength w with 50nm sampling intervals.

The coefficient of determination R^2 was used to test the stability of the established model, and the root mean-square error($RMSE$) was used to test the capacity. Results showed that R^2 is 0.78 and $RMSE$ is 0.431

for calibration, R^2 is 0.81 and *RMSE* is 0.402 for validation**.** Fig.3 shows the predicted versus observed values for the soil organic matter content predicting model. The result is comparable to previous researches [4].

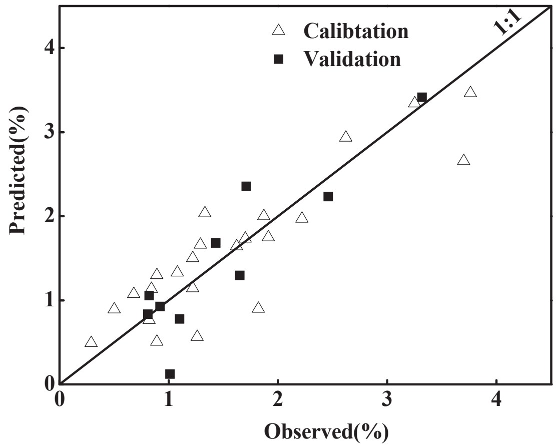

Fig. 3 The plots of predicted versus observed SOM

Hyperspectral remote sensing is a simple and nondestructive analytical method that can be used to predict soil organic content. The main challenge limiting application of hyperspectral remote sensing is choosing suitable data pretreatment and calibration strategies. In this study, derivative analysis was used as an effective tool to analyze hyperspectral data and detected spectral features. Then stepwise multiple linear regression was used to correlate reflectance data and soil organic content with soil samples collected in western Jilin province, China. The results show that this technique can be used to estimate SOM content. Since that this study was mainly supported in laboratory, the problem we have to be face with is how to apply this technique to support field-scale analysis of SOM. What' more, considering that soils in western JiLin have the distinct spectra as they contain more alkaline saline soils, the model developed in this study may not be appropriate for other areas. However, it is certain that hyperspectral remote sensing has the potential to be used as a rapid soil testing technique for precision soil management and assessing SOM.

4. REFERENCES

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