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The Contrast of Selecting Wavelength Capability of SPA and GA for Soil EC Detecting Model

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Abstract. The electrical conductivity(EC) of the soil was an important index to evaluate soil salinity. Spectral detecting method was an effective method. The objectives of this study were to compare choosing ability of the successive projections algorithm (SPA) and Genetic Algorithm (GA) methods for sensitive wavelengths and establish hyper spectral inversion model. Firstly, 140 soil samples were taken back to the laboratory and measured the EC (soil: water=1:5, EC1:5) and spectral reflectance(900-1700nm). Secondly, the SPA and GA were used to select sensitive wavelengths for reducing the complexity of the model, then PLSR method was used to establish detecting model. Finally, the determination coefficient (R^2), root-mean-square error (RMSE), ratio prediction to deviation (RPD) and the number of wavelengths selected were used to evaluate different kinds of methods. The experimental results showed the prediction models after using SPA were better than GA method because SPA had lesser band number and time, higher R^2 and RPD, smaller RMSE(band number=5, R^2=0.9707,RPD=8.4445 and RMSE=0.31178). Thus, it was validated the SPA method can be used to select sensitive wavelengths to improve the model accuracy of soil EC.

1. Introduction

Soil salinity is one of the most serious global environmental problems[1] and the problem has become worse and worse[2]. Especially, the problem of salinization is more serious in Xinjiang province of China[3]. Increased soil salinization directly affects soil aggregation, hydraulic conductivity, water and fertility absorption[4-5]. However, the field measurements of soil salinity require extensive time, cost and experiences. Thus, quickly and directly estimating soil salinity have become increasingly important[6]. Remote sensing monitoring method has become the most important large-scale monitoring method. Although the electrical conductivity(EC) and salt content can reflect the degree of soil salinity, the nature of reflecting soil salinization are very different. In addition, the spectral difference is obvious because the soil structure and ion composition are different in different regions. The EC reflects the amount of ions or molecules in the soil, and the salt content reflects the quality of the ions or molecules in the soil. It is undefined the response mechanism of high spectral information to soil salinization is the quality of ions and molecules or salt content[7]. Generally, soil salinity can be calculated by EC easily measured. So, EC is also used to evaluate soil salinization[7]. Establishing hyperspectral quantitative inversion model of EC is an important content of soil salinization monitoring, which uses the indexes or sensitive spectral bands to obtain satisfactory inversion results[1].

These main methods of getting EC are summarized as follows: (1) using EC indices derived from specific bands, band ratios and other combinations[7-10], such as NDVI[8 9 10], NDSI and SAR[10] (2) using indirect indicators associated with plant reflectance[11].

However, no matter using what kind of quantitative modeling method of the EC(Such as PLSR, MLR) and preprocessing methods(such as Log(R), Log(1/R)), derivative, normalization, linear baseline correction, multiplicative scatter correction(MSC), savitzky golay smoothing and correlation coefficient method) [7]. Because the spectral dimension of hyper spectral data is bigger and there is a certain correlation between different bands. So wavelength selecting methods are usually used to screen sensitive wavelengths to increase efficiency of the detecting model, such as Successive projections algorithm(SPA) and Genetic Algorithm(GA). So, the paper focuses on comparing wavelength selection ability of SPA and GA methods for the detecting of EC in Southern Xinjiang. The research results can provide reference for selecting sensitive bands and the remote sensing monitoring of EC in Southern Xinjiang.

2. Materials and methods

2.1. Research Area

The experiment was designed at Akesu area in Southern Xinjiang(East longitude 81° 53'45", north latitude 40° 20'18"). The average temperature is 10.5℃, annual average highest temperature is 18℃, accumulated temperature above 10℃ is 4113℃, frost-free period is 220 days, the sunshine is 2900 hours every year, average sunshine from April to October is 9.5 hour, the average annual rainfall is 49 mm. The jujube trees in the research area were seasonally affected by soil salinity because groundwater levels rise close to the soil surface.

2.2. Soil sample Description

In the research area, soil samples were collected from agricultural fields cultivated with jujube tree. Salinization problems were serious and can affect jujube yield. Because deep soil has less impact on reflectance of near infrared spectrum. 140 soil samples in different area were collected from 0-5cm.The samples were taken back to the laboratory, then grounded and sieved (2 mm) to reduce the effect of surface roughness. Finally, 140 soil samples were obtained. 100 soil samples were chosen by random sampling to use for the training set. The remaining 40 samples were used for the validation set.

2.3. Electrical conductivity and spectral reflectance measurements

The soil EC data were obtained in the laboratory by using a bench conductivity meter with a range between 0 and 20 ms•cm-1(DDSJ-308A). The EC was measured from the 1:5 dilution extract (soil sample: distilled water)[7]. The spectral reflectance measurements of the soil samples were acquired by using a near infrared hyperspectral device (GaiaSorter spectrometer, ZOLIX, Beijing, China). The GaiaSorter spectrometer mainly includes uniform lighting, spectral cameras, electronic mobile platform (or conveyor belt), computer and control software. The wavelength range is 900-1700nm. The spectral resolution is 3nm. Each soil sample was measured five times, the reflectance values were obtained by using built-in software to calculate the average value of five spectral curves.

2.4. Data analyses methods

First of all, SPA and GA methods were used to select the feature variables(sensitive bands) for reducing the complexity of the model. Then, PLSR method was used to establish detecting model. Finally, selected wavelength number, R^2, RMSE and RPD were used to evaluate GA and SPA methods. All methods were implemented in MATLAB 7.11.0.

3. Results and discussion

3.1. Spectral Reflectance of the Soil electrical conductivity

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Table 1 showed the descriptive statistics of the EC that had a mean value of 5.494 ms•cm-1, a max value of 10.54 ms•cm-1, a min value of 0.272 ms•cm-1 and a standard deviation of 2.731 ms•cm-1. Figure 1 showed reflectance spectrum of the soil samples (950-1750nm) increased at the different wavelengths with different values of soil EC. Spectral curve trend of all kinds of samples were consistent(Fig 1). And, the existing research showed that soil main ions included Cl^-,Na+ and Ca+ in the Southern Xinjiang, the three kinds of ions were the dominant factor of EC values[3]. In addition, the Cl^-, Na+ and Ca+ can produce absorption bands(absorption valley) between 1320nm and 1500nm. So the differences of EC spectral reflectance value were obvious, and there were obvious absorption valleys between 1320nm and 1500nm.

Table 1 Statistics of the soil electrical conductivity

Statistical index	Mean	Maximum	Minimum	Standard deviation
Electrical conductivity($ms \cdot cm^{-1}$)	5.494	10.54	0.272	2.731

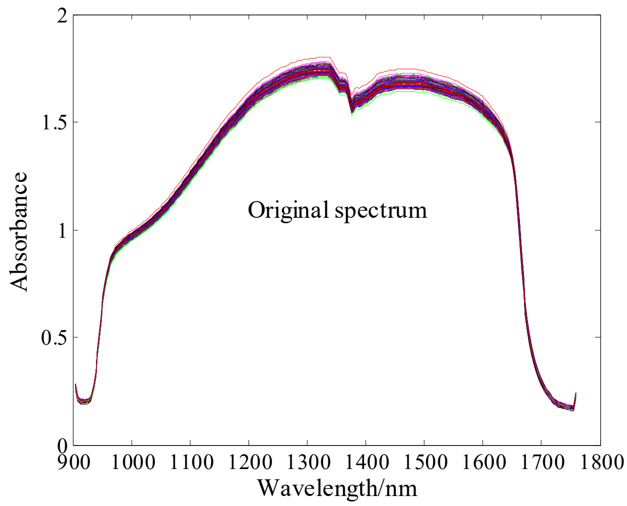

Fig 1 Original spectrum

3.2 The contrast of selecting wavelength capability of SPA and GA

Different detecting models were respectively established by using original spectrum+SPA+PLSR and original spectrum+GA+PLSR based on the calibration dataset(100 samples). We then validated the model by using an independent validation dataset(40 samples). SPA and GA selecting spectral bands was shown as fig 2. It can be seen that GA method selected 40 wavelengths and SPA method selected 5 wavelengths.

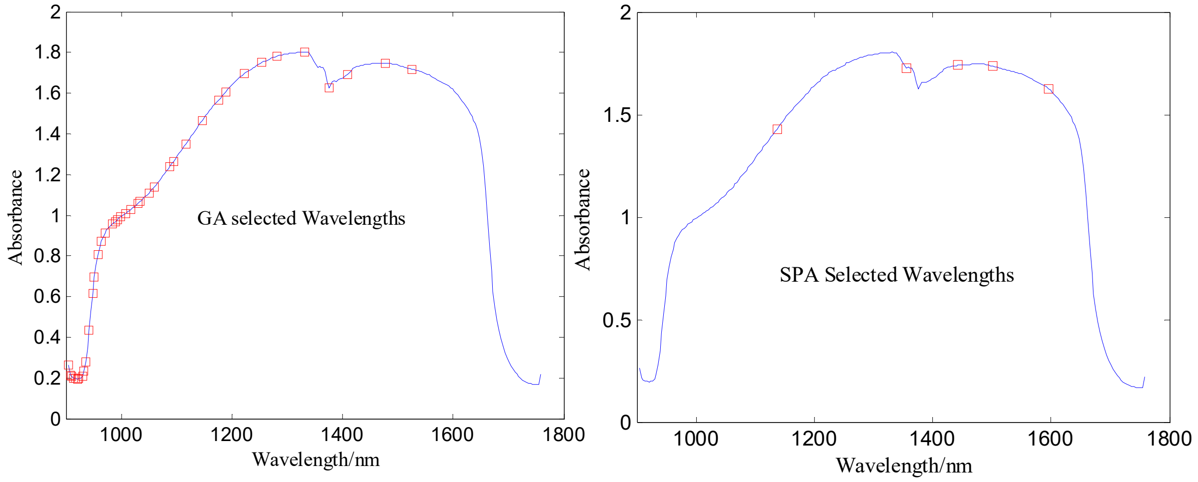

Fig 2 Selected wavelengths of GA and SPA methods

The predicted scatter diagram based on SPA and GA was shown in fig 3. The predicted points were scattered around the 1:1 line. Compared SPA and GA method, although the R^2 of two methods are higher than 0.95, RPD are higher than 6 and RMSE are smaller than 0.4. The prediction models after using SPA were slightly improved than GA. But the wavelength number of SPA was less than the GA method. In fact, it takes more time to run the GA program(more than 2 minutes). The SPA method takes only 20 seconds.

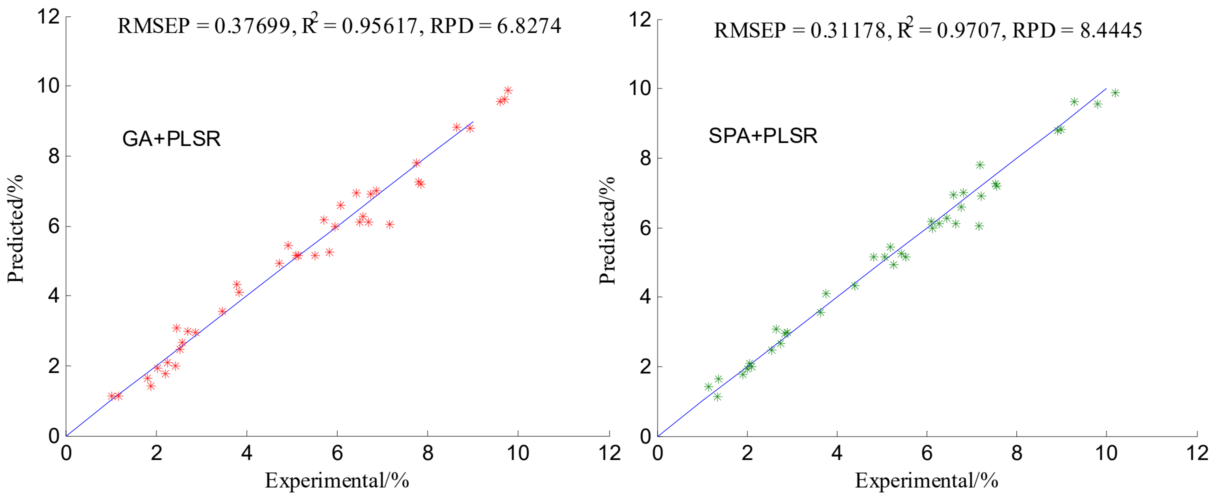

Fig 3 PLSR Prediction model of EC

4. Conclusions

The research focused on that analyze hyperspectral response of EC of arable soil between 900 and 1750 nm in the laboratory, validate choosing ability to sensitive wavelengths of SPA, GA and establish hyperspectral inversion model. Experimental results show that the wavelength screening ability of SPA was better than GA method. The wavelength number of the SPA+PLSR model is 5, R^2=0.9707,RPD=8.4445, and RMSE=0.31178.

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