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Soil Heavy Metal Inversion based on Hyperspectral Remote Sensing Technology

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Abstract

In this study, the contents of Cr in 44 soil samples were collected. ASD FieldSpec HR (350 ~ 2500 nm), and then the NOR, MSC and SNV of the reflectance were pretreated, the first deviation, second deviation and reflectance reciprocal logarithmic transformation were carried out. Comparing the reflection characteristics of different heavy metal contents and the effect of different pretreatment methods on the establishment of soil heavy metal spectral inversion model. The results show that: (1) Combining differential transformation can improve the information of heavy metal elements in the soil. (2) The modeling accuracy of the optimal model of nine heavy metal spectra of Cr by PLSR were 0.7002.

Keywords

Reflectance spectra; soil heavy metals; partial least squares regression; visible-near infrared.

1. Introduction

In recent years, domestic and foreign scholars have made extensive research on the use of hyperspectral inversion of soil organic matter, nitrogen, phosphorus and potassium, and less research on heavy metal content estimation [1]. Used the partial least squares regression model to estimate the cadmium and zinc contents in the Rhine basin. The regression model of heavy metals in the soil was established by different differential transformations combined with partial least squares regression and multiple stepwise linear regression [2-3]. The results show that there was a correlation between Fe, Zn and Xi and the reflectance spectrum in the soil of Fuyang River in the visible-near infrared range.

There were different soil types in different regions, different degrees of pollution, showing different spectral characteristics, the establishment of the prediction model was obvious. Therefore, based on the characteristics of soil reflectance spectrum in the study area, a variety of pretreatment and comparative analysis of the established inversion model can establish accurate estimation model of heavy metal element content. In this study, nine kinds of heavy metal elements in Fufeng County, Yangling County and Wugong County of Shaanxi Province were used as target attributes, and normalization (NOR), Multiplicative Scatter Correction (MSC), standard normal variable transformation (SYV) was reconstructed by Standard Normal Variate (SNV). Combining with the Savitzky - Golay convolution smoothing method, the spectral

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curves were smoothed and denoised, and the first deviation, second deviation and reciprocal logarithmic differential transformation were combined.

2. Materials and Methods

2.1. Sample Collection and Determination of Elemental Content

The soil samples were collected according to the "S" -shaped sampling method. The sampling depth was the thickness of the tillage layer, usually 0-30cm. A total of 44 soil samples were sampled. The samples were air-dried and passed through the 2 mm hole. A 200 g soil sample was mixed and passed through a 100 mesh sieve for indoor heavy metal content and another soil sample was used for soil reflectance spectroscopy. Soil samples were digested with 4: 1 (v / v) HCl and HNO3. The content of heavy metal elements was determined by inductively coupled plasma emission spectrometry (ICP-MS, Agilent 7700)

Table 1. Statistical result of heavy metal elements for soil samples

Elements	Samples	Maximum (mg/kg)	Minimum (mg/kg)	Mean (mg/kg)	Standard deviation(mg/kg)	Coefficient of variation
Cr	44	20.0	16.1	18.0	0.9582	0.0958

2.2. Page Numbers Measurements of Spectral Reflectance

The reflectance of 20 samples of soil samples was measured using the ASD FieldSpec4 Spectrometer. The wavelength range of the spectrometer was 350 ~ 2500 nm, the sampling band width was 1.3 nm (350 ~ 1000 nm) and 2 nm (1000 ~ 2500 nm), and the sampling intervalwas1 nm, totaling 2150 bands. The samples were filled with 2 mm diameter sieve and slabed with a diameter of 6 cm and a depth of 1.5 cm. The spectral reflectance was measured. When measuring the rotation of the dish 3 times, each rotation angle of 90 degrees, to obtain four directions (each direction to collect 5) a total of 20 spectral reflectance curve.

2.3. Excluding Outliers

Soil samples in the collection, processing and analysis process will introduce different degrees of error, will affect the late data analysis and modeling accuracy. The Mahalanobis distance was based on the multiple normal distribution, taking into account the covariance, mean and variance of the three factors, can be a comprehensive response to soil samples of the comprehensive indicators (Shi et al., 2014). Therefore, the anomalies of soil properties and spectral data were measured by Mahalanobis distance method.

2.4. Measurements of Spectral Reflectance

The original spectral data of all soil samples were processed using ViewSpecPro, and the arithmetic mean of the spectra after removing the outliers was taken as the actual reflection spectrum of the soil. Due to the difference in the energy response of the spectrometer, there was a breakpoint at 1000 nm, and the spectral curve was used for breakpoint repair using Splice Correlation (Fig. 1). Normalization (NOR), Multiplication Scatter Correlation (MSC), Standard Normal Variate (SNV) were used to eliminate the scattering between soil samples using TQ Analyst. Caused by the impact.

2.5. Differential Transformation

The original spectral data of all soil samples were processed using ViewSpecPro, and the arithmetic mean of the spectra after removing the outliers was taken as the actual reflection spectrum of the soil. Due to the difference in the energy response of the spectrometer, there was a breakpoint at 1000 nm, and the spectral curve was used for breakpoint repair using Splice Correlation. Normalization (NOR), Multiplication Scatter Correlation (MSC), Standard Normal

Variate (SNV) were used to eliminate the scattering between soil samples using TQ Analyst. Caused by the impact.

3. Results and Discussion

3.1. Overview of the Study Area

In this study area, 44 soil samples were collected. Among them, the soil pH value between 7.47 ~ 8.38, belonging to alkaline soil. The first, second deviation and reflectance reciprocal logarithmic transformation were used to analyze the correlation of nine kinds of heavy metal elements. The results were shown in Fig.2. Compared with the original reflection spectrum, the reflection spectrum of the differential transformation, the correlation significantly improved. The correlation coefficients of second deviation of Cr and reflectance spectra were -0.61. The reflectance spectra of soils can be distinguished from the absorption characteristics after differential transformation, and enhance the correlation between heavy metal elements and reflectivity.

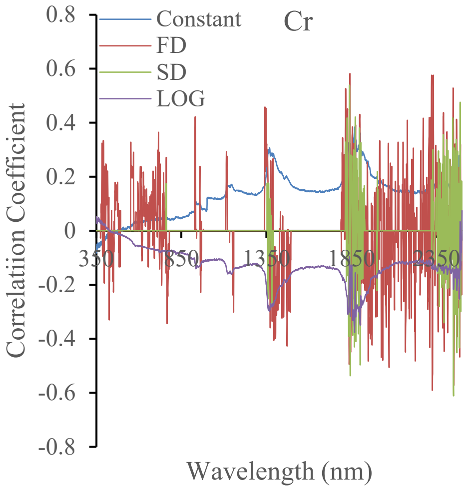

Fig 1. Correlation coefficient between nine heavy metals and reflection spectra

Table 2. The result of PLSR based on different pretreatment methods

Elements	Methods	Calibration			Validation	
		Rc^2	RMSEC	P_c	Rv^2	RMSEP
Cr	S+C	0.6188	0.753	3	0.5182	0.716
	C+FD	0.7895	0.588	3	0.6205	0.687
	C+SD	0.5944	0.771	1	0.6814	0.709
	C+LOG	0.6151	0.756	3	0.5523	0.730
	NOR+S	0.6315	0.743	3	0.5501	0.733
	NOR+FD	0.5408	0.804	1	0.3931	0.806
	NOR+SD	0.5653	0.791	1	0.7294	0.720
	NOR+LOG	0.6300	0.744	3	0.6133	0.697
	MSC+S	0.3650	0.892	1	0.7404	0.698
	MSC+FD	0.7580	0.625	2	0.6195	0.693
	MSC+SD	0.6082	0.761	1	0.6865	0.706
	MSC+LOG	0.6778	0.705	3	0.5090	0.753
	SNV+S	0.6003	0.766	2	0.6545	0.674
	SNV+FD	**0.7002**	**0.684**	**1**	**0.7450**	**0.595**
	SNV+SD	0.6065	0.762	1	0.6263	0.746
	SNV+LOG	0.6040	0.764	2	0.6566	0.670

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4. Conclusion

The reflection spectra were processed by NOR, MSC and SNV respectively. The first, second deviation and reflectance reciprocal logarithmic transformation were used to reduce the influence of external factors. The At the same time, the differential transformation can help to improve the correlation between the heavy metal elements and the reflection spectrum in the soil, and the use of the higher correlation band can significantly improve the stability and prediction ability of the model.

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