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Application of Remote Sensing in the Estimation of Soil Organic Matter Content

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This paper uses remote sensing technology to estimate the content of soil organic matter. It samples the soil, test its organic matter content, and analyzes the correlation between the reflectance of bands of various wavelengths and the content of organic matter in the soil with modern remote sensing technology. It figures out changes of soil organic matter content in different forms, and on which basis, determine the sensitive band of organic matter and construct an estimation model for the estimation of soil organic matter content at multi bands and single band. It finds that there is a close relationship between soil organic matter content and each band, and the estimation model is sound in stability and accurate measurement. As the application of remote sensing technology can improve the accuracy of the estimation of soil organic matter content, it is worth promotion and application.

1. Introduction

Organic matter is an important part of soil, and it is also one of the key indicators to the soil fertility level and soil's reflectance spectrum. Although the content of organic matter accounts for 10% or less of the total content in soil, its value is undeniable. Organic matter is essential to the production of agriculture, the protection of soil environment and the growth of plants. It is a key factor in ensuring the quality of soil and the healthy growth of plants. Therefore, when estimating the content of organic matter in soil, we must ensure the efficiency and accuracy of such estimation. Only in this way can we increase the economic benefits of agriculture, farmers and provide an important reference for the promotion of sustainable agriculture. Traditional soil organic matter content estimation method is high in cost and low in efficiency. In the actual application, the accuracy of the estimated data is often affected by the geographical location. With the development of agricultural technology, the traditional estimation method can no longer meet the requirements of precision agriculture, hence the emergence of remote sensing technology. Thanks to its advantages in the time segments of data acquisition and rich information contained in remote sensing images, remote sensing technology is widely used in soil composition, estimation, and inspection. Statistics show that the spectral characteristics of organic matter are mainly reflected in its ability to absorb visible light, which also indicates that the content of organic matter in soil is related to the reflectance and near-infrared wavelengths in visible light. Therefore, the reflected spectrum of soil can be fully used to reflect the content of organic matter.

2. Literature review

Soil surface organic matter content is an important soil property of soil mapping, interpretation of soil properties and agricultural fertilization. How to obtain the content of soil organic matter directly with remote sensing image becomes a hot topic in soil research. According to the theory of electromagnetic waves of matter, any substance has a strict physical mechanism for the generation of its spectrum. As its inherent properties reflect, absorb, project, and radiate electromagnetic waves, soil surface organic matter content serves as the basis for remote sensing interpretation and analysis of surface targets. Castaldi et al. (2016) pointed out that the diversity of soil constituents and the unique spectral characteristics of each component in the soil make the spectra of various soils have their own characteristics. A study of the relationship between soil constituents (such as moisture, organic matter, iron oxides, clays, etc.) and soil reflectivity measured

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under laboratory conditions shows that: the spectral characteristics of soil have a clear relationship with the physical and chemical properties of the soil and can reflect the properties of soil to some extent with the soil spectrum. Grinand et al. (2017) studied the land in the Palouse area of eastern Washington State and used TM-band ratios to judge the exposure of ancient soils due to erosion in the study area. The authors analyzed the benefit of using the ratio of the wavebands to suppress the effects of different brightness values and atmospheric reflections caused by the slopes. In the study, organic carbon mapping was performed on summer fallow with the 1/4, 3/4, and 5/4 band ratios of TM data. In the study area, the ratio of 3/4, 5/4 and 5/3 bands were used to determine the free iron/carbon content to estimate the erosion status of paleosols, so as to determine whether aviatic remote sensing images of bare soil can be used to estimate soil organic carbon content. Jin et al. (2016) selected 28 sampling sites in the experimental field in 115ha in Crisp County, Georgia, southern United States, the statistical relationship between the surface soil organic carbon content and the aerial image red, green, and blue band image brightness values was analyzed, and a logarithmic equation was established to predict the surface organic carbon content. Nawar et al. (2016) used the historical hierarchical foreground and background analysis (HFBA) method to identify soil properties in two valleys in the Santa Monica Mountains, California. The idea of the method is to extract spectral information from different grades of soil chemical composition differences and obtain a series of training vectors in sequence with HFBA methods. These vector values are used in AVIRIS images to determine organic matter and iron content. This method gradually narrows the range of differences in soil characteristics and finds some of the characteristics of small absorption spectra that are directly related to soil properties. This method can be used for soil classification in laboratory and AVIRIS images. The results show that the classification results have a good prediction effect. Vegetation and relatively steep topography in the study area influence the judgment of soil properties. Sadeghi et al. (2015) used digital photographic systems to photograph bare soil in two regions of the Midwestern United States. The purpose of this study is to determine that soil lines containing image brightness values in the red and near-infrared bands can be used to map organic matter in topsoil and provide guidance for soil sampling. The author firstly brings the brightness values of all pixels in the study area into the formula: $NIR=\alpha R+\beta$ to calculate the brightness values of the minimum points of the red and near infrared bands in the soil line; then calculates the Euclidean distance between the brightness value of each pixel and the minimum point of the soil line; finally, the relationship between Euclidean distance along the soil pixel and the content of organic matter in surface soil is obtained. Schuur et al. (2015) improved the method of determining soil line parameters with the extracted features of artificial extracted bare soil pixels, an automatic soil line identification procedure is developed from bare soil remote sensing images to obtain soil line parameters. The key to the automatic discriminator is the user-defined band width and the size of the original subset used for the iterator. Comparing the two extraction methods, the automatic extraction method is considered simpler and easier. Sharma et al. first conducted a spectral test on the collected soil in the laboratory and analyzed the shape of the reflectance spectrum determined by the soil organic matter content in the range of 0.35 μm to 1.4 μm. Therefore, the author determined the shape of the continuous spectral curve of the soil by treating the coefficient of the polynomial of degree 3 as a parameter. This method for predicting organic matter content in TM or ETM images requires some modification of the parameters and calculate the spectral reflectance values at 1.049 μm, 1.258 μm, and 1.467 μm to calculate the polynomial coefficients. Were et al. (2015) analyzed the relationship between the compositional content (all-iron, organic matter, titania, alumina, and silica) taken from three important soil types in central Brazil and the reflectance values of the soil in AVIRIS images. Since the study collected black-red tropical soils rich in opaque minerals (such as iron oxide and titanium oxide), these opaque minerals reduced the soil reflectivity and masked the absorption band characteristics produced by other components: the difference in soil organic matter content in the visible light range produces only a small change in the spectrum, so the correlation between reflectivity and organic matter content is poor.

In summary, the above studies are mainly on the estimation of soil organic content, but also the application of remote sensing data in the content of soil, but the study is relatively simple. Therefore, based on the above research status, the application of remote sensing in soil organic matter content estimation is mainly studied. Remote sensing and soil science are analyzed, remote sensing data are collected and analyzed, and an inversion model of soil properties and specimen collection are established. The results show that the prediction model established with remote sensing technology can more accurately determine the soil organic matter content.

3. Method of the research

Based on the hyperspectral technique and the main properties of the soil, the spectra of wheat field and soil organic matter are obtained to (1) analyze, with winter wheat tests for two consecutive year, the response relationship between organic matter and spectrum in the wheat field, evaluate the feasibility of using near-infrared spectroscopy to monitor soil nutrients in wheat field soils; (2) systematically and comprehensively study the effect of conventional spectrum, conversion spectrum and calibration treatment on the accuracy of soil organic matter monitoring in wheat fields, comprehensive assess the optimal pretreatment plan of spectral data to lay a foundation for the accurate and comprehensive mining and extraction of spectral feature information; (3) fully and systematically extract the spectral characteristics of the organic matter of the oil of wheat field based on the spectral information of the organic matter extracted with continuous projection algorithm; (4) use the modeling in multiple linear regression to construct a spectrum monitoring model of wheat field soil organic matter and the spectral bands at full scale to construct a spectrum monitoring model of wheat field soil. In addition, use continuous projection algorithm to extract and mine the hyperspectral information of the soil in the wheat field, and multivariate linear regression to construct the hyperspectral monitoring model. Compare the modeling effects of the two models. Table 1 shows the definition of hyperspectral remote sensing.

Table1: Definition of hyperspectral remote sensing

Spectral resolution	Band number (1)	△y/y	VNIR	MIR	IRT
multispectral	5-10	0.1	50-100	100-200	1000-2000
hyperspectral	100-200	0.01	5-20	10-50	100-500
hyperspectral	-	0.001	0.1-5	0.2-10	20-100

4. Research results and discussion

4.1 Remote sensing technology and soil science

Spectral reflectance as one of the basic properties of soil will change with soil’s physical and chemical properties. The parent material of the soil, its organic matter content, moisture, and surface roughness will all affect the spectral reflectance of the soil. They form the physical basis of soil remote sensing technology, and provide a new way for excavating soil properties and a new indicator for the quantitative inversion of soil properties. The rise of remote sensing technology was first to meet the needs of soil science, one of the major service object for modern remote sensing technology. As remote sensing data present geographic information within a region, it enables the monitoring and comparison of different landscape elements in a wide area, and record them as basis for changes. Since these elements can reflect the distribution and characteristics of different soils either individually or in combination, traditional remote sensing data have greatly supplemented soil science. With the continuous deepening of the research on soil remote sensing and the gradual upgrade of sensors, especially with the advent of hyperspectral remote sensing, soil remote sensing has ushered in the research on quantitative detection of soil material components. The analysis of soil spectrum will facilitate the detection of surface or shallow surface soil properties with hyperspectral remote sensing data, as well as the construction of various types of analytical models based on field measurements.

4.2 Remote sensing data acquisition

The study adopts Hyperion L1R data. The imaging time was 02:17 UTC on May 22, 2012, and the image was located between 25°38'44.05〃N and 26°3924.43^N, 117°20'22.09"E and 117°38'58.85irE. Please refer to Figure 1 for the image.

Figure 1: Map of Hyperion data

Pretreatment of remote sensing images refers to various technical processes that need to be performed on the images or data acquired by remote sensing, so that they are more suitable for application [94]. It can make the image more clear, highlight target features against the background, and facilitate information extraction in the computer. It can restore the original image, enhance the processing of the image, and perform automatic identification and information extraction. The problem waveband rejection, the reserved bands and their wavelength in the whole process are shown in Table 2.

Table 2: Problem bands removal

Excluded band		Retention periods.	
Hyperion's original band.	Wavelength range (nm)	Hyperion's original band.	Wave length fan enclosure (nm)
1 month 7 days	355.59*426.82	8-87	426.82-884.7
58-78	892.28-993.17	79-120	996.63-1346.25
121-130	1356.35-1447.14	131-165	1457.23-1800.29
166-180	1810.38-1951.57	181-223	1961.66-2385.4
224-242	2395.5-2577.68		
Total: 72 bands.	Total: 170 bands.		

4.3 Construction of soil property inversion model

The paper uses L1R image data of Hyperion. It screens the type of land cover in remote sensing images of soil survey samples, and brings exposed soil and vegetation cover screened to the construction of a soil property inversion model. Extract the spectral information of the pixel where the sample is located and process the spectrum. Use unary linear regression analysis and stepwise regression analysis to establish an estimation model of soil property and content based on full wave bands and significant bands.

4.4 Sample collection

The climate, hydrothermal conditions of the sample collection area good and conducive to plant growth will have an uncertain impact on the retrieval of soil properties using remote sensing images. The paper uses support vector machine to classify remote sensing images, where the separation degree of vegetation and soil is 1.96, of residential area and soil, 1.99, and of vegetation and residential area, 2 (sample separation parameter is between 0 and 2, and is fine when greater than 1.9). Cross extract remote sensing image classification results and fuzzy clustering results, and conduct superposition extraction when the effects of clouds, shadows, water bodies, residential areas, and more complex features on the images removed. Select soil survey samples in the exposed soil pixels and vegetation pixels, 103 and 525 respectively. Randomly choose 80 and 23 from the former as modeling samples and verification samples respectively, and 485 and 40 from the latter as modeling samples and verification samples respectively. Figure 2 shows Hyperion hyperspectral spectral curves of exposed soil pixels and Figure 3 shows that of vegetation pixels.

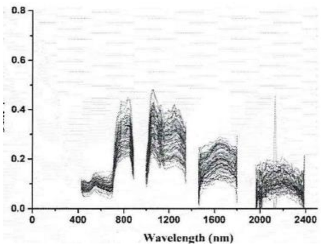

Figure 2: Exposed soil coverage sample spectrum original reflectance

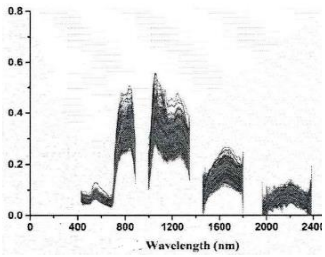

Figure 3: Vegetation coverage Sample spectrum original reflectance

We can see from Figure 2 that the reflectance of 400-2400 nm is low, and increases first and then decreases at 700-1300 nm. In Figure 3, the reflectance at 400-700 nm is not more than 0.1, and clearly peaks at 500-600 nm in the strong reflection peak area of chlorophyll. The reflectance shows a sharp upward trend at 700-1300 nm, and nearly linear at 700-750 nm, with slope related to the content of chlorophyll (a+b) per plant leaf area. 1470 nm and 2000 nm are bands of strong absorption of water and C02, hence the trough. Table 2-2 shows the soil property and content information of modeled exposed soil and vegetation pixel samples.

Table 3: Information of nutrient content by soil samples

Like yuan type	Sample points (1)	The soil properties	The minimum value	The maximum	The average	The standard deviation	Variation coefficient %
soil	80	Alkaline hydrolysis nitrogen (mg/kg)	77	31.5	165.96	46.25	27.87
		Organic matter (g/kg)	12.4	59.8	35.73	12.3	34.42
		Effective phosphorus (mg/kg)	1	212.7	42.14	40.79	96.80
		Rapidly-available potassium (mg/kg)	19	424	100.03	68.42	68.40

Table 4: Information of nutrient content by soil samples (continued)

Like yuan type	Sample points (1)	The soil properties	The minimum value	The maximum	The average	The standard deviation	Variation coefficient %
vegetation	485	Alkaline hydrolysis nitrogen (mg/kg)	30	499	149.83	43.98	29.35
		Organic matter (g/kg)	9.6	64.3	30.66	9.95	32.45
		Effective phosphorus (mg/kg)	0.1	331.5	41.17	46.23	112.29
		Rapidly-available potassium (mg/kg)	13	91.9	92.84	86.78	93.47

It can be seen that in the soil pixels and the vegetation pixels, the differences in the soil properties of the soil samples are not obvious, with coefficient of variation highest in available phosphorus and lowest in alkaline dissolved nitrogen. It indicates that there is a large degree of dispersion between available phosphorus samples and a small degree of seperation between alkaline dissolved nitrogen samples. Among them, when the coefficient of variation of available phosphorus content in vegetation pixels is more than 100%, it is a strong variability. Figure 4 and Figure 5 are the first derivative curves of the reflectance of the exposed soil pixel samples and the vegetation pixel samples respectively.

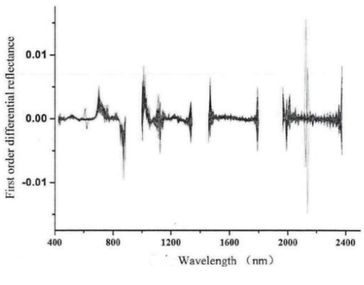

Figure 4: First order derivative reflectance of exposed soil coverage samples

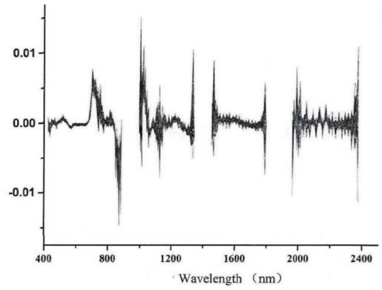

Figure 5: First order derivative reflectance of vegetation coverage samples

5. Conclusion

This paper introduces remote sensing technology in the estimation of soil organic matter content, builds an effective estimation model, and reaches the following conclusions: (1) Given the high content of organic matter in the soil, and with its increase, the color of the soil gets from light to dark, the soil spectrum reflectivity reduces, therefore, the prediction model established with remote sensing technology is more accurate. (2) The high probability of soil phosphorus being fixed by soil minerals is manifested in the soil mineral composition image band. Therefore, the inversion model constructed with modern remote sensing technology can predict the results both timely and accurately. (3) Considering the geographical conditions of strong reflection, it is appropriate to construct a prediction model of available phosphorus based on the vegetation pixels, which also shows that there is a very close relationship between the available phosphorus content and its spectral response.

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