Evaluating soil parameters with visible spectroscopy

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Abstract: Using spectroscopic techniques, correlation analysis and regression were conducted between soil parameters and visible reflectance spectra of raw soil samples. The samples were collected in a cornfield with lower moisture content and a forage field with higher moisture content. Five soil parameters, soil moisture, SOM, NO_3-N, EC and pH, were analyzed by conventional method in a laboratory. Visible reflectance spectra of the samples were measured by a spectrophotometer. The spectral variable used was the first derivative of visible reflectance. Results showed that all five soil parameters could be evaluated by visible reflectance. In the cornfield with lower moisture (< 30% db), a single linear regression model was available for moisture estimation, and a multiple exponential model was recommended to evaluate NO_3-N. However, it failed to establish the evaluating model of SOM because of its small variation, and it was difficult to obtain the estimation model of EC and pH because of lower moisture content. In the forage field with higher moisture (> 70% db), a multinomial model with single variable was better for moisture estimation, and a single linear model and two multiple linear models were recommended to evaluate SOM, EC and pH respectively. For NO_3-N, a multiple exponential model was also recommended. It would be necessary to study the correlation between visible reflectance and soil parameters of raw soil samples with middle moisture (30%～70% db).

Key words: precision agriculture; soil parameters sensing; visible reflectance; spectroscopy
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1 Introduction

Precision agriculture is a management approach to variations in the field, such as soil parameters, yields, weeds, insects, in order to adjust agricultural inputs to the site specific requirements. Describing the variability of soil parameters is an important step for promoting precision agriculture. Hence it is necessary to look for a real-time evaluating method of soil parameters.

Many spectroscopic approaches, mainly near infrared (NIR) spectroscopic approaches, have been introduced in soil parameters evaluating. Krishnan et al analyzed the correlation between soil organic matter (SOM) and NIR spectral reflectance over 800～2400 nm wavelengths, and developed a multiple linear regression model using 1100, 1350, 1398 and 2210 nm wavelengths with correlation coefficient of 0.934[1,2]. Sudduth and Hummel evaluated CEC and SOM using a portable NIR spectrophotometer in the laboratory[3～5]. Reeves, III et al analyzed agricultural soils by NIR spectroscopy[6,7]. Analyzed parameters were pH, total C, total N, active N, biomass N, and mineralisable N. Evaluating models for these parameters showed high R-Square.

However, above studies provided the dried and crushed soil samples in the experiment in order to eliminate the influence of moisture and particle size of soil samples. So that the results obtained could not be directly used to real-time evaluate soil parameters. Li Minzan et al carried out a series of the experiments to raw soil samples in order to develop a real-time soil spectrophotometer[8,9]. NIR spectra of the soil samples were measured rapidly after sampling without any treatment. Soil parameters analyzed were soil moisture, SOM, nitrate nitrogen (NO_3-N), electric conductivity (EC) and pH. Results showed that it was possible to evaluate those five soil parameters with the NIR spectral reflectance. And it was also shown that the first derivative of the reflectance spectrum was more effective for fitting the regression models.

Meanwhile, it was also reported that visible reflectance spectra could be used for evaluating soil parameters[10,11]. Since elements and instruments for measuring visible light have simpler structure and cheaper price, it would be easier to develop real-time soil sensor with visible spectral reflectance than that with NIR spectral reflectance. Therefore it is necessary to explore correlation between soil parameters and visible reflectance spectra of raw soil samples collected from field in order to develop real-time soil sensor.

The aim of this study is to reveal the possibility

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evaluating soil parameters with visible reflectance spectra of raw soil samples using spectroscopic approach and statistic analysis, and then to construct the theoretic and practical basis for the development of real-time soil sensor.

2 Methods and materials

2.1 Soil samples

Two fields, a cornfield and a forage field were selected for the study. 15 soil samples were randomly collected from the layers of topsoil 0～10 cm depth in the cornfield with lower moisture content (< 30% db). And 25 soil samples were randomly collected from the layers of subsoil 20～30 cm deep in the forage field with higher moisture content (> 70% db). Soil texture was 20% clay, 34% silt, 46% sand for the cornfield soil, and 20% clay, 28% silt, 52% sand for the forage field soil. Both of them were classified into CL.

2.2 Methods

The desktop spectrophotometer UV-3100PC, Shimadzu Ltd., was used for measuring spectral reflectance of the soil samples. It has 250～2500 nm measurable range in 2 nm resolution and 20 nm band width. Since the aim of this study is to reveal the possibility evaluating soil parameters with visible reflectance spectra, only 400～800 nm of reflectance spectra were analyzed here.

Collected soil samples were directly provided for spectral analysis and moisture measurement, and then for analysis of other soil parameters. Moisture was measured by 105℃- 24 h method with the electric oven heater. SOM was defined here by ignition loss after burning at 800℃ for 3 h in the electric muffle oven. NO_3-N, EC and pH were measured with portable NO_3-N meter C-141, EC meter B-173 and pH meter B-212, made by Horiba Ltd., respectively. Incorporate 5 g air dried soils into 25 g distilled water, and then shake it for 30 minutes, and then take the top clear solution for measurement of NO_3-N, EC and pH.

Although visible reflectance spectra could be used for the correlation analysis and regression analysis, the first derivative of the original spectral reflectance was thought more effective since it might eliminate some systemic errors, such as the fluctuation of light source, the change of distance from light source to the surface of soil samples. Thus in this study the first derivative of the visible reflectance was selected as spectral variable.

The first derivative was calculated by Eq. (1) developed by Shibusawa S. et al[12].

$$y_i = \frac{1}{6h}(-11x_i + 18x_{i+1} - 9x_{i+2} + 2x_{i+3}) \quad (1)$$

Where, y_i is the first derivative; x_i is the visible reflectance; h is the sampling interval (2 nm).

3 Results and discussion

3.1 Data processing

3.1.1 Soil parameters

Table 1 shows the statistic characteristics. The soil samples in the cornfield were low moisture soil with low EC values while the soil samples in the forage field were high moisture soil with high EC values. NO_3-N, SOM and pH showed similar variations. In addition, SOM was higher than common soil samples, which usually changed from 1% to 6%.

Table 1 Statistic characteristics of soil parameters in the test fields

Parameters	Cornfield			Forage field		
	Min～Max	Mean	Std. deviation	Min～Max	Mean	Std. deviation
Moisture/%	2.9～25.4	13.2	5.6	72.3～108.0	95.7	8.8
NO_3-N/mg·(100 g)$^{-1}$	3.1～11.3	5.4	2.1	3.2～13.6	6.0	2.3
SOM/%	21.2～23.3	22.3	0.7	18.6～27.1	23.7	2.4
EC/μS·cm^{-1}	72～190	128	36	148～280	220	34
pH	6.5～7.4	7.0	0.2	6.0～6.6	6.3	0.2
Texture	20% clay, 34% silt, 46% sand			20% clay, 28% silt, 52% sand		

3.1.2 Visible reflectance spectra

The soil parameters and soil type of 4 examples were shown in table 2. Four examples of visible reflectance spectra and its first derivative were shown in Fig. 1. The original spectra had no obvious peaks and spike drops, and simply increased alone with wavelength went up. For the first derivative, it had some peaks (428 nm, 542 nm, 746nm) and spike drops (460 nm, 592 nm). The result showed that there were some special absorptions within 400～800 nm though the absorption mechanism could not be clearly understood yet as NIR[13～15]. Furthermore, both in original reflectance and the first derivative, the difference of spectra among different samples was observed. It showed that to evaluate soil parameters with visible reflectance would be possible and feasible.

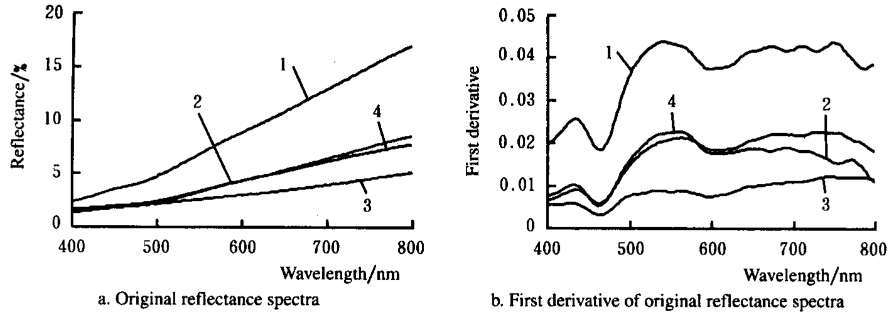

Fig. 1 Visible reflectance and its first derivative

Table 2 Soil parameters and soil type of 4 examples shown in Fig. 1

Spectrum number	Field	Sample number	Moisture % (db)	NO_3-N /mg · (100 g)$^{-1}$	SOM /%	EC/μS · cm^{-1}	pH
1	Cornfield	6	10.5	6.55	21.8	83.0	7.1
2	Cornfield	15	20.3	4.18	21.2	180.0	7.2
3	Forage field	1	72.3	8.93	25.7	250.0	6.0
4	Forage field	15	108.0	3.62	21.9	194	6.6

3.1.3 Data treatment

Firstly the wavelength area of 400～800 nm was divided into four parts, 400～500, 500～600, 600～700, and 700～800 nm. Then, the sum of reflectance in each part was calculated respectively, i.e. four data were obtained for each sample. Table 3 gives the new data of the samples shown in Fig. 1.

Table 3 New spectral data of the samples shown in Fig. 1

Wavelength /nm	Sample 6 in cornfield	Sample 15 in cornfield	Sample 1 in forage field	Sample 15 in forage field
400～500	1.18	0.420	0.257	0.445
500～600	2.06	0.973	0.418	1.03
600～700	2.03	1.02	0.479	0.916
700～800	2.07	1.08	0.589	0.805

Defined a calculated sum as a datum $x_{i,j,k}$, here i represents test field, $i = 1$: cornfield and $i = 2$: forage field; j represents the sequence of soil sample, for cornfield $j = 1～15$ and for forage field $j = 1～25$; k represents the sequence of the wavelength area, $k = 1, 2, 3, 4$ corresponding with wavelength area of 400～500, 500～600, 600～700, and 700～800 nm respectively. Based on above definition, next eight data sets were obtained, $\{x_{1,j,k}, j = 1, 2, \cdots, 15\}$, $k = 1～4$ and $\{x_{2,j,k}, j = 1, 2, \cdots, 15\}$, $k = 1～4$.

Finally, the correlation analysis and regression were carried out between each soil parameter and each data set.

3.1.4 Check of correlation coefficients

Correlation coefficients between each soil parameter and each new data set were checked. Table 4 shows the result. The highest correlation was observed between soil moisture and the data set (500～600 nm) in the cornfield. And the lowest correlation was also observed in the cornfield between SOM and the data set (700～800 nm). Using these coefficients, it was performed to fit evaluating models of all soil parameters.

Table 4 Correlation coefficient between soil parameters and data set of visible spectral reflectance

	400～500 nm	500～600 nm	600～700 nm	700～800 nm
Cornfield				
Moisture	-0.960	-0.965	-0.955	-0.913
SOM	-0.044	-0.069	-0.068	-0.032
NO_3-N	-0.334	-0.343	-0.369	-0.441
EC	0.110	0.034	-0.048	-0.125
pH	-0.290	-0.305	-0.315	-0.294
Forage field				
Moisture	0.578	0.608	0.628	0.786
SOM	-0.890	-0.886	-0.878	-0.748
NO_3-N	-0.361	-0.380	-0.389	-0.471
EC	-0.824	-0.836	-0.833	-0.799
pH	0.663	0.665	0.679	0.801

3.2 Moisture

It was observed that the correlation coefficients between soil moisture content and the new spectral data was negative in the cornfield, while there was positive correlation in the forage field. Next hypothesis was given to explain the fact.

For the cornfield, since moisture content was lower (< 30% db), soil moisture mainly existed as molecular state, and combined with soil particle tightly. When soil moisture content went up, the color of soil would become dark, so that more light might be absorbed by soil. In other words, reflecting light from soil sample surface would decrease as soil moisture increased. However for the forage field, since moisture content was very high (> 70% db), soil moisture mainly existed as small drip, and formed a water film in the surface of soil sample like a mirror. As soil moisture went up, the "mirror" would become smoother so that reflecting light would increase.

Regressions were conducted. Figure 2 shows the single linear models of the cornfield and the forage field. For the cornfield it has a good fitting between test data and evaluating model. The best model shown in Fig. 2a was obtained between the moisture content and data set $\{x_{1,j,2},\ j = 1, 2, \cdots, 15\}$.

For the forage field, although coefficients obtained were comparatively high, they were not high enough to evaluate soil moisture directly. Using all four data sets a multiple linear regression was executed, and a high correlation coefficient of 0.858 was obtained. Meanwhile, single variable model is always expected better for evaluating because of its high stability. Thus, the correlation between soil moisture and data set in the forage field was examined again by drawing data plot. Fig. 2b shows the plot of data set $\{x_{2,j,4},\ j = 1, 2, \cdots, 25\}$. It was obvious that linear model was not suitable to the data. After a series of calculation, a multinomial model shown in Fig. 2b was obtained. The R-square was improved to 0.710, and good fitting between test data and evaluating model was observed. It would be more suitable than a multiple linear model.

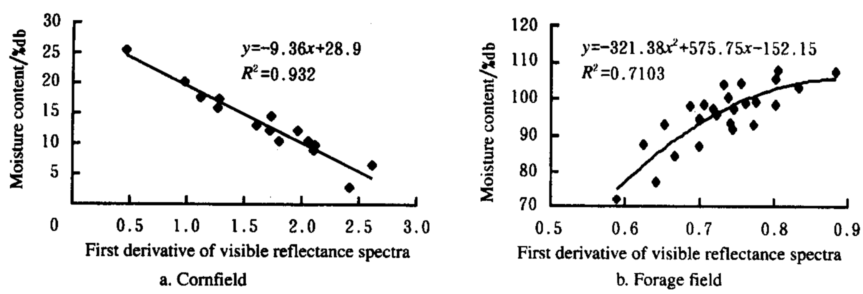

Fig. 2 Regressive models of soil moisture

3.3 SOM

In the forage field, quite high correlation was observed between SOM content and visible reflectance. The highest coefficient was obtained in the data set $\{x_{2,j,1},\ j = 1, 2, \cdots, 25\}$. Fig. 3 shows the data plot and the regressive model. The SOM content could be well evaluated by visible reflectance spectra.

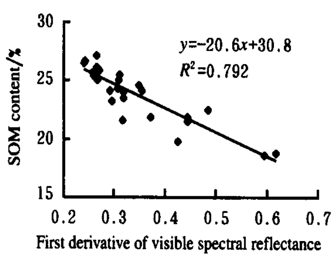

Fig. 3 Regressive model of SOM in the forage field

However, the coefficients between SOM and visible reflectance were too small to execute multiple-regression in the cornfield. One of the possible reasons was small variation of SOM data. Its variation coefficient (σ/μ) was only 0.003. For this small variation, visible spectral reflectance could not have enough sensitivity to differ from the difference of SOM content. It was necessary to intentionally collect soil samples with great variation in SOM content in order to get suitable estimation model.

3.4 NO_3-N

As shown in table 4, the single correlation coefficients between NO_3-N content and each data set were lower. For both the cornfield and the forage field, multiple linear regressions were performed. However all estimation models obtained were not significant. Thus, it was necessary to conduct non-linear regressions. Various models were tested. Finally, an exponential model defined by Eq. (2) was determined.

$$C_N = a_0 + \sum_{i=1}^{4} a_i \exp(b_i x_i) \tag{2}$$

Where, C_N is NO_3-N content; x_i is the first derivative of visible reflectance; a_0, a_i and b_i are model coefficients; i is the number of data set. Since the model was non-linear, the model parameters were estimated with genetic algorithm.

Table 5 shows the regression result of the exponential model. High coefficients of 0.900 and 0.836 were obtained. It made it clear that NO_3-N content, an important soil nutrient parameter, can be evaluated by visible reflectance.

In addition, the models had comparatively many model coefficients as shown in table 5. It might result in model diverging. Thus it would be necessary to conduct more experiments and tests to reduce the number of model coefficients.

3.5 EC

From table 4, high correlation (negative) between EC and visible reflectance was observed in the forage field, while there was no significant correlation in the cornfield.

Table 5 Regressive coefficients of evaluating models for NO_3-N

Model	$y = a_0 + \sum a_i \exp(b_i x_i)$ $(i = 1 \sim 4)$								
Wavelength /nm	Cornfield					Cornfield			
		400~500	500~600	600~700	700~800		400~500	500~600	600~700	700~800
Model Coefficient	a_0: 4.38					a_0: 4.37				
	a_i	-15.2	-7.53	-2.68	2.62	a_i	2.18	8.86	-7.97	-17.5
	b_i	-11.4	3.62	-14.0	-11.4	b_i	-7.99	-18.2	6.35	12.1
Correlation Coefficient	0.900					0.836				

EC depends on many kinds of ions concentrated in soil. When soil moisture was higher as the forage field, ions in the soil would be very live. And the concentration difference of ions might result in the change of light absorption or reflectance. Conversely, when soil moisture was lower as the cornfield, ions in the soil would be not live and the ion concentration would also be quite low. Thus it would be difficult to identify the difference of ions concentration using visible reflectance in dry field.

A multiple linear regression was conducted to the forage field. The result (Fig. 4a) shows a good fitting between tested data and estimated data.

3.6 pH

pH is also an integrated soil parameter relating to H^+. It also showed some correlation with soil moisture as EC. High positive coefficients were observed in the forage field with higher moisture but in the cornfield with lower moisture. It seems difficult to evaluate pH in low moisture soil with visible reflectance.

Regression analysis between pH and visible reflectance in the forage field was conducted in the similar way to EC estimation, and the result, with high correlation coefficient of above 0.880 (R^2 = 0.780), was shown in Fig. 4b.

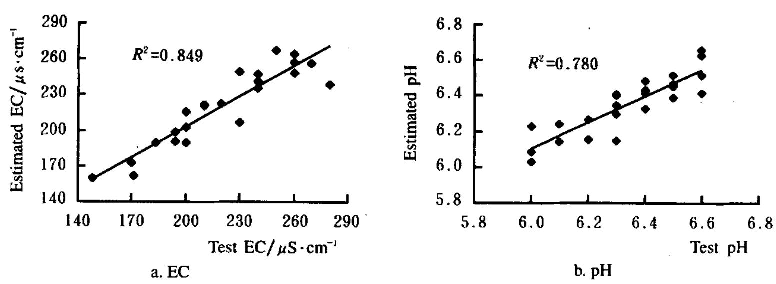

Fig. 4 Regressive result of EC and pH in the forage field

4 Conclusion

It was studied to evaluate soil parameters with visible reflectance spectra of raw soil samples. The soil samples were collected from a cornfield and a forage field, and the soil parameters analyzed were soil moisture, SOM, NO_3-N, EC and pH.

In the cornfield with lower moisture (< 30% db), a single linear regression model was available for moisture estimation, and a multiple exponential model was recommended to evaluate NO_3-N. However, it failed to establish the evaluating model of SOM because of its small variation, and it was difficult to obtain the estimation model of EC and pH.

In the forage field with higher moisture (> 70% db), a multinomial model with single variable was better for moisture estimation, and a single linear model and two multiple liner models were recommended to evaluate SOM, EC and pH respectively. For NO_3-N, a multiple exponential model was also necessary.

Meanwhile, it would be necessary to study the correlation between visible reflectance and soil parameters of raw soil samples with middle moisture (30%～70% db).

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基于可见光光谱分析的土壤参数分析

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摘　要: 利用光谱分析技术, 进行了农田原始状态土壤样品的可见光光谱与土壤参数之间的相关、回归分析。土壤样品采集于一块水分较低的玉米地和一块水分较高的牧草地, 所分析的土壤参数有土壤水分、土壤有机质含量、土壤硝态氮含量、土壤电导率以及土壤pH 值, 土样的可见光光谱由精密分光光度计测量。分析结果显示, 有效的光谱特性值为反射光谱的一次微分, 所有5 个土壤参数都可以利用土样的可见光光谱特性进行分析和检测。对于土壤水分、土壤有机质含量、土壤电导率以及土壤pH 值, 线性模型是有效的; 而对于土壤硝态氮含量, 则需要利用多元指数模型进行分析或检测。

关键词: 精细农业; 土壤参数检测; 可见光反射率; 光谱学