2018

SHAANXISHENG TUDI GONGCHENG JIANSHE JITUAN BAIPIAN YOUXIU LUNWENJI

陕西省土地工程建设集团
百篇优秀论文集

《陕西省土地工程建设集团百篇优秀论文集》编委会 编

陕西新华出版传媒集团
陕西科学技术出版社
Shaanxi Science and Technology Press

陕西省土地工程建设集团
百篇优秀论文集

（2018）

《陕西省土地工程建设集团百篇优秀论文集》编委会　编

陕西新华出版传媒集团
陕西科学技术出版社
Shaanxi Science and Technology Press
西　安

图书在版编目(CIP)数据

陕西省土地工程建设集团百篇优秀论文集. 2018/
《陕西省土地工程建设集团百篇优秀论文集》编委会编.
—西安：陕西科学技术出版社,2019.12
ISBN 978－7－5369－7656－6

Ⅰ. ①陕…　Ⅱ. ①陕…　Ⅲ. ①土地开发－中国－文集
Ⅳ. ①F323.211－53

中国版本图书馆 CIP 数据核字(2019)第 215827 号

陕西省土地工程建设集团百篇优秀论文集(2018)

出版者　陕西新华出版传媒集团　陕西科学技术出版社
西安市曲江新区登高路 1388 号陕西新华出版传媒产业大厦 B 座
电话（029)81205187　传真（029）81205155　邮编 710061
http: //www.snstp.com

发行者　陕西新华出版传媒集团　陕西科学技术出版社
电话(029)81205180　81206809

印　刷　陕西天地印刷有限公司

规　格　880mm×1230mm　开本　16

印　张　48

字　数　1400 千字

版　次　2019 年 12 月第 1 版
2019 年 12 月第 1 次印刷

书　号　ISBN　978－7－5369－7656－6

定　价　200.00 元

《陕西省土地工程建设集团百篇优秀论文集(2018)》
编辑委员会

前　言

土地是人类赖以生存与发展的重要物质基础。在人口、资源、环境与发展(PRED)复合系统中,土地资源始终居于其他资源无法替代的核心地位。随着工业化和城镇化的快速推进,土地资源的质量严重影响到区域可持续发展和人居环境改善。在推进生态文明和建设美丽中国的背景下,如何确保粮食安全,实现人居环境与经济协调发展,成为全社会关注的核心议题。

陕西省土地工程建设集团(以下简称“集团”)以工程技术实际需求为驱动力,以土体有机重构为核心,研究开发了“砒砂岩与沙复配成土技术”“盐碱地‘改排为蓄’治理模式”“城市边缘区废弃土地整治技术”等多项土地工程理论与技术,促进了土地科技的发展。截至目前,累计实施土地整治工程总规模近 5.33 万 hm^2,新增耕地约 3.33 万 hm^2,建设高标准农田约 1.33 万 hm^2,修复城市土地约 1.33 万 hm^2,累计工程节约支出超 50 亿元,经济社会生态效益显著。

2018 年,集团瞄准世界科技前沿,不断强化前瞻性基础性研究,推进土地工程高层次科研平台建设,为土地科技创新提供了基础保障。国家自然资源部退化及未利用土地整治工程重点实验室评估获优秀、国家土地工程技术创新平台培育基地进入首批自然资源部工程技术创新中心序列、集团科研团队入选陕西省“三秦学者”创新团队、集团院士专家工作站列入陕西省省级院士专家工作站。“大众创业、万众创新”,集团员工立足工作岗位,创新工作思路,全年以第一作者共发表论文 1100 余篇,其中 SCI 14 篇,EI 90 篇。每一篇论文都是作者在参与土地工程科研及土地整治工程实践中求真务实、凝练真知的结果。集团全年度获批发明专利 4 项,实用新型专利 20 项,软件著作权 9 项。科研攻关、技术研发为工程实践奠定了理论基础,也标志着集团科研能力再迈新台阶。

为推进土地工程学科建设,加强土地工程理论成果的交流推广和工程应用,本着质量优先的原则,编委会从集团 2018 年公开发表的论文中筛选出 100 篇编纂成集,希望能为从事土地工程及相关领域的科研人员、管理工作者提供参考。本论文集内容涉及土地信息与土地资源、土地整治工程、土地利用与保护、房地产及建筑工程、矿业类和综合管理六大类,理论研究联系工作实际,直接为生产管理服务。本论文集在编辑过程中以尊重原著为前提对原文做了适当调整,并按其内容和议题类别予以分类编排,以便阅读。论文评审委员会以毛忠安总工程师为组长,吴晔、张宏凯、罗林涛、王欢元等诸位专家给出了中肯有效的评选意见,本论文集才得以完成。编辑过程中,张扬、陈科皓、席慧、刘雨沛、姚丝思等人以高度的责任心和严谨的工作作风,全身心投入,付出了大量心血。本书得以出版,还得到陕西科学技术出版社的热情支持,在此,一并表示衷心的感谢!

编者

2019 年 10 月

目　　录

1　土地信息与土地资源

2　土地整治工程

3 土地利用与保护

4 房地产及建筑工程

5　矿业类

6　综合管理

1　土地信息与土地资源

Prediction of Soil Organic Carbon with Different Parent Materials Development Using Visible-Near Infrared Spectroscopy

Liu Jinbao[1,2,3,4], Han Jichang[1,2,3,4], Zhang Yang[1,2,3,4],
Wang Huanyuan[1,2,3,4], Kong Hui[1,2,3,4], Shi Lei[1,2,3,4]

(1. Shaanxi Provincial Land Engineering Construction Group, Xi'an 710075, China;2. Key Laboratory of Degraded and Unused Land Consolidation Engineering, the Ministry of Land and Resources, Xi'an 710075, China;3. Institute of Land Engineering and Technology, Shaanxi Provincial Land Engineering Construction Group. Xi'an 710075, China; 4. Shaanxi Provincial Land Consolidation Engineering Technology Research Center, Xi'an 710075, China)

【Abstract】The storage of soil organic carbon (SOC) should improve soil fertility. Conventional determination of SOC is expensive and tedious. Visible – near infrared reflectance spectroscopy is a practical and cost – effective approach that has been successfully used SOC concentration. Soil spectral inversion model could quickly and efficiently determine SOC content. This paper presents a study dealing with SOC estimation through the combination of soil spectroscopy and stepwise multiple linear regression(SMLR), partial least squares regression(PLSR), principal component regression(PCR). Spectral measurements for 106 soil samples were acquired using an ASD FieldSpec 4 standard-res spectroradiometer (350 ~ 2500 nm). Six types of transformations and three regression methods were applied to build for the quantification of different parent materials development soil. The results show that (1)The basaltic volcanic clastics development of SOC spectral response bands located in 500 nm, 800 nm; Trachyte spectral response of the soil quality, and the volcanic clastics development at 405 nm, 465 nm, 575 nm, 1105 nm. (2)Basaltic volcanic debris soil development, first deviation of maximum correlation coefficient is 0.8898;Thick surface soil of the development of rocky volcanic debris from bottom reflectivity logarithm of first deviation of maximum correlation coefficient is 0.9029. (3) Soil organic matter content of basaltic volcanic clastics development optimal prediction model based on spectral reflectance inverse logarithms of first deviation of SMLR. Independent variable number is 7, $Rv^2 = 0.9720$, $RMSEP = 2.0590$, $sig = 0.003$. Trachyte qualitative volcanic clastics developed soil organic matter content of the optimal prediction model based on spectral reflectance inverse logarithms of first deviation of PLSR. Model number of the independent variables $Pc = 5$, $Rc = 0.9872$, $Rc^2 = 0.9745$, $RMSEC = 0.4821$, $SEC = 0.4906$, forecasts determine coefficient $Rv^2 = 0.9702$, $RMSEP = 0.9563$, $SEP = 0.9711$, $Bias = 0.0637$.

【Key words】Basalt; Trachyte; Soil organic carbon; Deviation; Hyperspectral prediction model

1　Introduction

Soil organic carbon (SOC) is an important component of land ecosystem and evaluate soil fertility. It is of great significance in the quantitative research of soil organic carbon in land use, soil mapping [1-4]. The traditional soil organic carbon determination method takes time and laboriously, and can't obtain the needed soil monitoring data in time. Hyperspectral remote sensing technology has unique advantages in the prediction of SOC content because of its characteristics of time – saving, low – cost, less sample required, no destructive sample structure and abundant information. Soil spectroscopy has shown to be a fast, cost-effective, environmental – friendly, nondestructive, reproducible, and repeatable analytical technique[5,6]. Gomez et al (2008) showed that SOC contents were predicted by partial least – squares regression (PLSR) using both the proximal and remote sensing spectral[7]. By obtaining the spectral data of soil samples and combining the chemical data measured with the physical model to establish the relationship between soil properties and quantifying soil information, it has been widely used in the field of rapidly obtaining soil SOC content [8-11], providing a broad prospect for understanding soil spectral information and content prediction.

In recent years, domestic and foreign scholars have established soil spectral data and quantitative organic carbon quantitative mathematical models for different study areas, different soil types, and different modeling egression methods[12-14], indicating that the prediction accuracy of local spectral models is always higher than that of remote-site models. Different types of soils have different soil types and complex soil components. Different soil components show different spectral characteristics due to the influence of soil mineral components, and the differences between the two models are significant. The physical and chemical properties of soils formed on different parent materials are also different. Only by determining the same mineral components in soil can an accurate prediction model of SOC content be established. The study shows that the parent material will significantly affect the spectral characteristics of the soil, and the interpretation of the spectral inversion model of the soil parent material will be more explanatory [15,16]. Lokuhewage et al, 2005 used to estimate spectral absorption of mixed sample waters containing the four elementary algae and DOC by multiple linear regression analysis[17]. Principal component analysis for all spectral pretreatments satisfactorily identified the clusters by compost types[18,19] Therefore, in this study, the SOC of the rough rock and basaltic volcaniclastic matter in northeastern China was taken as the target attribute. Hyperspectral reflectance of soils developed from rough rock and basaltic pyroclastic was measured by using Savitzky – Golay convolution smoothing method for the original spectral curve smoothing, denoising[20], the original spectral reflectance of the first deviation, second deviation, reciprocal differential, reciprocal logarithmic first deviation and reciprocal logarithm The second deviation transformation was used to analyze the correlation between SOC content and SOC content. The data were analyzed using the methods of Stepwise multiple linear regression (SMLR), Principal Component Regression (PCR) and Partial least squares regression(PLSR) to establish SOC content prediction model.

2 Materials and Methods

2.1 Soil Inventory and Analyses

For this study,106 soil samples of different parent materials development were used for spectral analysis, include 42 samples of trachyte, basalt number 64. The samples were air – dried, removed crop residues, root material and sieved to pass through 2 mm mesh. The SOC content was measured by taken from a 0.149 mm pore sieve for 30 mg and analyzed using the Walkley – Black procedure. (Table 1).

Table 1 The statistics of soil organic carbon

Parent material	Max($g \cdot kg^{-1}$)	Min($g \cdot kg^{-1}$)	Mean($g \cdot kg^{-1}$)	SD
Trachyte	11.14	0.16	2.89	2.65
Basalt	11.09	0.13	2.97	2.36

2.2 Spectrum Acquisition

The diffuse reflectance spectra of the samples were measured with a FieldSpec 4 standard – res spectroradiometer. The spectral range of 350 ~ 2500 nm, the sampling band width was 1.3 nm at 350 ~ 1000 nm and 2 nm at 1000 ~ 2500 nm. The spectral resolution of 3 nm at 700 nm, 8.5 nm at 1400 nm and 6.5 nm at 2100 nm. Measurement were made with a high – intensity contact probe (Analytical Spectral Devices) illuminated by a halogen bulb (2901 +/ – 10% k), the spot of diameter 10 mm. The soil samples were filled with 2 mm diameter sieve, slabed with a diameter of 6 cm and a depth of 1.5 cm. For each soil samples were collected 10 times and averaged to reduce mistake and to maximize the signal – to – noise ratio. The sampling interval was1 nm, so that each spectrum comprised reflectances at 2151 wavelengths. 70% samples out of soil samples were selected randomly as training set. The remaining 30% would represent test set.

2.3 Data Analysis

2.3.1 Signal Processes

Data analysis was conducted using the 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.

2.3.2 Deviation of Spectral

Different deviation processing methods were used to smooth and remove the influence of noises. Five deviations of soil spectral data could be calculated using the spectrum by using Savitzky – Golay convolution smoothing[21,22]. In addition to direct analysis of soil spectral reflectance, five transformations were made for finding the response regions of different parent materials. First deviation and second deviation transformations would increase the correlation between reflectivity and SOC elements while eliminating or limiting the influence of partial linearity or near linear background [23,24], where λ_i was the wavelength i nm band, $\Delta\lambda = \lambda_i + 1 - \lambda_i = 10$ nm, the first deviation $\rho'(\lambda_i)$ and the second deviation $\rho''(\lambda_i)$, $i = 400, 410, \cdots, 2450$ nm.

$$\rho'(\lambda_i) = [\rho(\lambda_{i+1}) - \rho(\lambda_{i-1})]\overline{\Delta\lambda} \tag{1}$$

$$\rho''(\lambda_i) = [\rho'(\lambda_{i+1}) - \rho'(\lambda_{i-1})]\overline{\Delta\lambda} \tag{2}$$

$$\lg\left(\frac{1}{\rho(\lambda_i)}\right) = -\lg\rho(\lambda_i) \tag{3}$$

$$\lg\left(\frac{1}{\rho(\lambda_i)}\right)' = -\lg\frac{\rho'(\lambda_i)}{\lg\rho(\lambda_i)} \tag{4}$$

$$\lg\left(\frac{1}{\rho(\lambda_i)}\right)'' = -\frac{\rho''(\lambda_i)\rho(\lambda_i) - [\rho'(\lambda_i)]^2}{\lg[\rho(\lambda_i)]^2} \tag{5}$$

Logarithmic transformation not only enhances the difference in visible spectrum, but also reduces the influence of multiplicative factors under light conditions, and logarithmically transforms lg $1/\rho(\lambda_i)$ for the spectral data.

2.3.3 Data Modeling and Validating

Because of soils are very complex, the spectra are actually a series of overlopping peaks. In order to characterize specific features, using correlation analysis SMLR, PLSR, PCR to build SOC content prediction models. Correlation were developed using The Unscrambler@ 9.7(CAMO Software releases). The coefficient of determination (R^2) between measured and predicted values, Coefficient of calibration (R_c) and Standard error of calibration (*SEC*) of calibration the stability of the model; the root mean square error (*RMSE*), Standard error of performance (*SEP*) of validation measured the quality of the model; Calculated as follows:

$$R^2 = \frac{\sum_{i=1}^{n}(\hat{y}_i - \bar{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y}_i)^2} \tag{6}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2} \tag{7}$$

$$SEC = \sqrt{\frac{\sum_{i=1}^{m}(y_i - \hat{y}_i)^2}{m - 1 - k}} \tag{8}$$

$$SEP = \sqrt{\frac{\sum_{i=1}^{n}(y_i - \hat{y}_i - Bias)^2}{n - 1}} \tag{9}$$

$$R_c = \sqrt{1 - \frac{SEC^2 \times (m - k - 1)}{SD \times (m - 1)}} \tag{10}$$

$$R_v = \sqrt{1 - \frac{SEP^2 \times (n - k - 1)}{SD \times (n - 1)}} \tag{11}$$

Where was the mean value of the sample observations, m was the number of samples for the calibration set, and n was the number of samples to be verified.

3 **Results and Discussion**

3.1 Reflectance Curves Analysis

The difference between the mean spectral reflectance and the corresponding continuum removal curve for the development of soils of rough and basaltic pyroclastic (Fig 1, Fig 2). Due to more soil samples, soil samples from different regions were selected. Due to the different parent materials, the reflectance curves of the spectral curves of soils developed and developed by two lithologic pyroclastic species are different in the range of 350 ~ 2500 nm. With the increase of SOC content, the reflectivity decreases in the wavelength range, and the curve becomes concave again by the convex straight line. The spectral reflectance of soils in basaltic pyroclastic was larger than that of the surface rock in pyroclastic pyroclastic matter, and the shape of the curve was quite different. The spectral curve of soil developed from basalt pyroclastic was in the range of 400 ~ 1300 nm. Within the range of 1440 ~ 1860 nm, the reflectivity shows a continuous increasing trend with the increase of the wavelength. Although the increase range is not obvious, it shows an increasing trend. In the range of 400 ~ 750 nm, the facies of the facies reflect a steep increase. The general trend of the facies in the range of 750 ~ 2450 nm is relatively flat with no significant change.

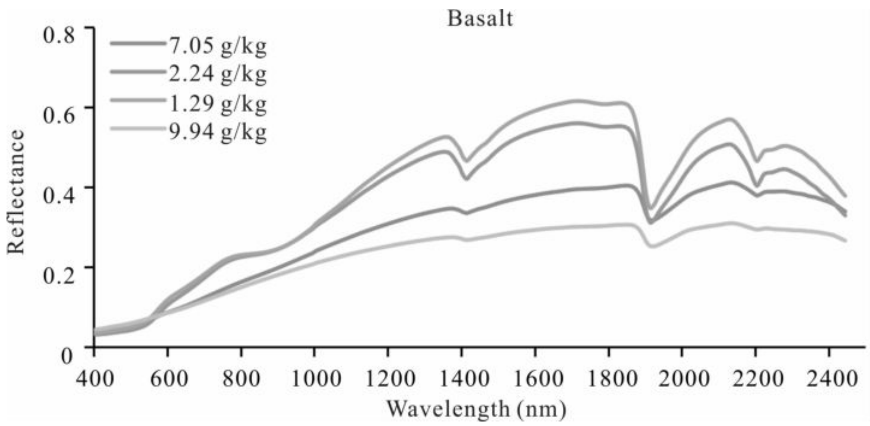

Fig. 1 Reflectance curves of basaltic different soil organic matter content

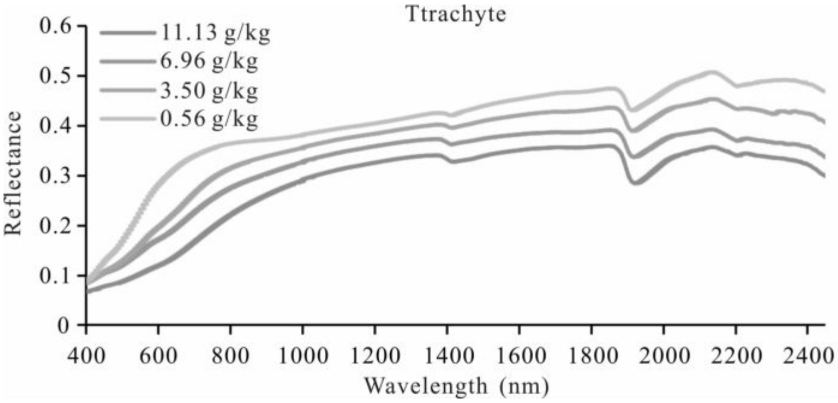

Fig. 2 Reflectance curves of trachyte in different soil organic matter content

Due to the wavelength dependence of organic molecules absorbed by C – O, C = O and N – H, electromagnetic wave affects soil reflectance in the visible (400 ~ 700 nm), near infrared (700 ~ 1400 nm) and shortwave infrared (1400 ~ 2500 nm) regions. Therefore, the spectral characteristics of soils developed from different parent materials are different, and the extracted characteristic bands are different, and the hyperspectral models of SOM content established are different.

3.2 Correlation Analysis

The results of correlation analysis between SOC content and spectral reflectance and their five transformations in two parental soil types in the range of 400 to 2450 nm. The maximum correlation coefficient between original reflectance and soil organic carbon content before conversion was –0.8887 and –0.3292 respectively. The maximum correlation coefficient between soil spectral reflectance and soil organic carbon content after first – deviation transformation of original spectral reflectance was at 665 nm and reaching the maximum at 2245 nm, respectively –0.8898 and –0.8896. Correlation analysis of spectral reflectance with soil organic carbon after second ~ deviation treatment showed that the maximum of correlation coefficient was in the near – infrared region, and the maximum value of correlation coefficient of organic carbon in soils of basaltic pyroclastic was at 815 nm. The maximum is 0.8114. The maximum of the correlation coefficient of the developed soil from the rough rock pyroclastic was at 1925 nm and the maximum was 0.7714.

After exponential logarithmic transformation of the original spectral reflectance, there was a good correlation between the organic carbon content of the basaltic pyroclastic detrital soil and each band, and the maximum value could reach 0.8596. The maximum correlation coefficients of spectral reflectance and soil organic carbon after the first log transformation of the original spectral reflectance reached the maximum at 2255 nm and 775 nm, which were 0.8683 and –0.9029, respectively. Correlation analysis of the second deviation of the logarithm of the reciprocal of organic carbon and reciprocal of spectral reflectance showed that the correlation coefficients of the two parent materials were highly significant. The maximum correlation coefficient of soil was 955 nm, and the correlation coefficient was 0.7509. The maximum correlation coefficient of the soil from the rough rock pyroclastic was at 1925 nm with a correlation coefficient of –0.8245. Comparisons of significance levels show that the significance level of soil organic carbon with different forms of spectral reflectance developed in basaltic pyroclastic matter is higher than that of the organic carbon in the soils developed by rough rock pyroclastic matter (Table 2).

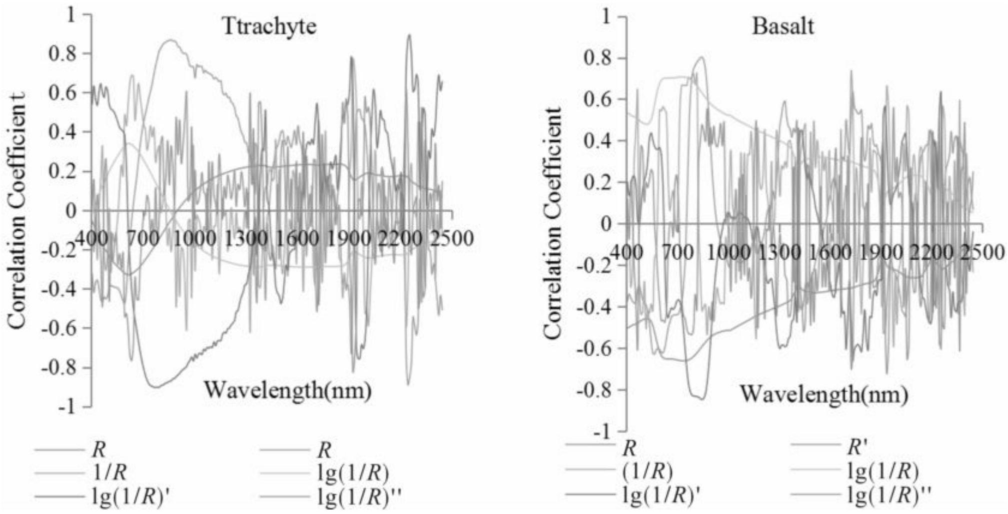

Fig. 3 Correlation analysis of SOC content and conversion of reflectivity different forms

Table 2 Correlation Analysis of Different Transformation of Soil Reflection Spectrum in Two Lithotic Volcanic

Types of spectral	Maximum correlation wave (nm)		Correlation coefficient	
	Basalt	Ttrachyte	Basalt	Trachyte
ρ	1235	615	-0.8887^{**}	-0.3292^{*}
ρ'	665	2245	-0.8898^{**}	-0.8896^{**}
ρ''	815	1925	0.8114^{**}	0.7714^{**}
$\lg(1/\rho)$	1145	615	0.8596^{**}	$0.3400*$
$\lg'(1/\rho)$	2255	775	0.8683^{**}	-0.9029^{**}
$\lg''(1/\rho)$	955	1925	0.7509^{**}	-0.8245^{**}

Note: * on behalf of the relevant at the 0.05 level, ** at the 0.01 level.

3.3 Establishment and Comparison of Spectral Regression Model

Correlation analysis and multiple stepwise regression analysis of SOC content and spectral reflectance and their different transformations can determine their sensitive bands. These sensitive bands have good correlation with organic carbon. Combined with the standardized regression coefficients, significant differences, the order of the various variables can indicate the sensitivity of the band size of SOC (Table 3).

The conclusion is that the SMLR model based on the first deviation of spectral reflectance has the best effect on the soil developed from the rough rock volcanic, with a determination coefficient of 0.9700 and RMSE of 2.2460 (Fig. 4(a)), R_{2245}, R_{2275}, R_{895}, R_{995}, R_{815}, R_{2395} and R_{965} have great correlations with SOC in the order of $R_{2245} > R_{2275} > R_{895} > R_{995} > R_{815} > R_{2395} > R_{965}$ and the best prediction model is $y = 4.90 - 16739.812R_{2245} + 4724.357R_{2275} + 96915.689R_{895} - 15939.403R_{995} - 33453.148R_{815} - 6064.713R_{2395} - 45543.196R_{965}$. Based on the SMLR model established by the first derivative of the logarithm of the reciprocal of spectral reflectance, the coefficient of determination was 0.9722 and the RMSE was 2.059 (Fig. 4 (b)), of which R_{2255}, R_{895} R_{2265}, R_{1415}, R_{2305}, R_{2035} and R_{1725} have great correlations with SOC, and the order of their size is $R_{2255} > R_{895} > R_{2265} > R_{1415} > R_{2305} > R_{2035} > R_{1725}$. The best prediction model is $y = 1.292 + 11242.085R_{2255} - 4519.379R_{895} + 12551.488R_{2265} - 6318.855R_{1415} - 9244.359R_{2305} - 5873.159R_{2035} + 9829.339R_{1725.}$