第8卷 第5期
2004年9月

遥 感 学 报
JOURNAL OF REMOTE SENSING

Vol. 8, No. 5
Sep., 2004

Article ID: 1007-4619(2004) 05-0434-09

Using Hyperspectral Data to Estimate Soil Surface Moisture under Experimental Conditions

LIU Wei-dong[1,2,3], F. Baret[2], ZHANG Bing[3], TONG Qing-xi[3], ZHENG Lan-fen[3]
(1. *Institute of Urban Meteorology, Beijing, CMA, Beijing 100089, China*;
2. *INRA, Bioclimatologie, Domaine Sanit-Paul, Site Agroparc, 84914 Avignon, Cédex 9, France*;
3. *Laboratory of Remote Sensing Information Sciences, Institute of Remote Sensing Applications,*
Chinese Academy of Sciences, Beijing 100101, China)

Abstract: Soil moisture is a very important variable in hydrologic cycle and exchange of matter and energy near ground boundary. It was investigated by the means of remote sensing due to a number of reasons. In this study, under experimental conditions, relationship between hyperspectral data and soil surface moisture has been investigated. Correlation between soil surface moisture for nine soil samples and four sets of spectral data of them (prototype reflectance, absorbance, the first-order derivative of reflectance and the first-order derivative of absorbance) was analyzed. We found that it has no obvious correlation between soil surface moisture and prototype reflectance and absorbance for all samples, while absorbance has higher correlation than reflectance. The first-order derivative of reflectance and the first-order derivative of absorbance have the obvious correlation near wavebands 1844 nm, and the first-order derivative of absorbance reflectance has more obvious correlation than the first-order derivative of reflectance. We choose these bands with high square of correlation coefficient to creat liner regression forecasting equation. Another nine soil samples were used to verify the precision of estimation equation. Results show that the first-order derivative of absorbance has the capability to estimate soil surface moisture of the four sets of data. It shows the great potential to estimate soil surface moisture within a large area for different soil types.

Key words: soil moisture; hyperspectral; derivative spectra; reflectance

CLC number: TP79 **Document code**: A

1 INTRODUCTION

Soil moisture is a key variable in hydrologic cycle and exchange of matter and energy near boundary. It has been widely used in many applications such as estimation of soil evaporation and susceptibility to wind erosion[1,2]. Measurement of soil surface moisture is an essential joint in these applications. Great effort has been expended looking for a simple and accurate way to measure soil moisture. Conventionally reliable approaches for estimation of soil moisture, such as gravimetry, neutron scattering, gamma attenuation and time-domain reflectometry, depend mainly on costly, time-consuming and intensive labor investigation in the field or on areal extrapolation of point measurements. In this way, in situ measurements of soil moisture are sparse and each value is only representative of a small area, frequently limiting utilization of these methods in large areas.

Remote sensing, if achievable with adequate accuracy and reliability, would provide truly meaningful capability to directly estimate soil moisture covering large areas within a short time period. In optical remote sensing, estimation of soil moisture was generally based on the effect of soil surface moisture on spectral reflectance. Already in 1925, Ångström's measurements

---

Received date: 2004-06-04

Foundation item: This paper was supported by the Scientific Service of the French Embassy in Beijing and Beijing Scientific Committee's Project "Study on the technology of Beijing Olympic game meteorological guarantee".

Biography: Liu Wei-dong(1973—), male, received the BA and M. Sc. degree from the department of meteorology in Beijing Agriculture University and the Ph. D. degree from the Institute of Remote Sensing Applications, Chinese Academy of Sciences. Since 2002, he has been employed as a researcher at Institute of Urban Meteorology, China Meteorological Administration. His research activities include urban ecology and urban remote sensing.

showed a decrease in reflectance after natural soils had been wetted by a shower[3]. He ascribed the reduction of the reflected light with moisture to total internal reflections on the water film covering the soil particles, which cause a portion of the energy to be reflected to soil itself. Curcio and Petty[4] reported that soil moisture affects soil reflectance due to water absorption bands at 760, 970, 1190, 1450 and 1940 nm and decreases the reflectance values throughout the entire spectra. In the laboratory, Bowers and Hanks' measurement demonstrated this appearance[5]. Stoner *et al*.[6] reported again soil moisture decreases the reflectance of soils and affects the shape of the spectra because of the occurrence of well-defined water absorption bands around 1400 nm and 1900 nm, especially for the brighter soils.

Based on the relationship between spectral data and soil surface moisture, several authors studied prediction of soil moisture. Bowers and Smith[7] reported a linear relationship between the intensity of this absorption band and soil water content. With near infrared data measured in laboratory for different soil samples, Dalal and Henry[8] predicted soil moisture by using an absorbance and got the standard error of prediction of 0.58%. Satellite data TM band 5 has also been used to estimate soil moisture content in northern Japan[9]. Although these approaches can be used for estimating soil surface moisture, the wavelength with the best coefficient of determination was dependent on the soil type. When these relations were applied to estimate surface moisture of other soils, it was difficult to get good result. Since the spectral characteristic of a soil is a function of the spectral characteristics of its individual components (soil moisture, organic matter, iron oxides, and clay mineral *et al*.) and the content and distribution of these components.

Generally, under certain illumination and observation conditions, moisture decreases soil reflectance throughout the entire spectra and affects the shape of the spectra because of water absorption wavebands around 1400 nm and 1900 nm, especially for the brighter soils[4, 6]. Organic matter has the similar effect to soil reflectance tends to decrease soil reflectance with increasing organic matter content in the range of 600—1100 nm[6, 10]. Iron oxide can induce the absorption features short of 1000 nm; Simmons[11] showed an inverse relationship between particle size and reflectance. Reflectance spectra of wet soils include prominent absorption bands centered at 1400 nm and 1900 nm, the bands at 1400 nm and 1900 nm are typically broad, indicating an unordered arrangement of water molecules at various site in the soil[12]. Increasing moisture content generally decreases soil reflectance across the entire shortwave. The experiments of Bowers and Hanks[5] are frequently cited to demonstrate decreasing spectral reflectance as a function of increasing moisture content for a silt loam soil. With prototype near infrared reflectance Whalley[13] estimated water content of soil. For the same soil, since moisture is the mainly affecting factor, using prototype reflectance to estimate can show its preponderance, however, most of the chosen wavebands to estimate soil moisture located in water absorption and out of atmosphere windows. So, it is difficult to gain precise estimation of soil moisture for different soil types with prototype reflectance. To different soils, the spectral effect of other soil characteristics frequently exceed the effect of soil moisture, thus using prototype reflectance to estimate soil moisture is constrained in uniform soil types.

To study soil surface moisture for different soils, we try to apply derivative hyperspectral data to study spectral effect of soil surface moisture. In the field of hyperspectral remote sensing, derivative analysis is a more promising approach to analyze remote sensing data. Derivative spectroscopy assumed that the components of variation are additive constants acting in a spectrally independent way over a spectral range of a few nanometers. And it uses the change in spectral radiance or spectral reflectance with wavelength to compute first order derivative or higher order derivatives[14]. Due to a number of advantages, derivative spectra has been widely applied into biophysical characteristics of vegetation and mineral estimation and soil organic matter estimating to sharpen the detail in absorption spectra. Gong[15, 16] used the first derivative spectra to recognize forest tree and estimate chemical components. Xiang[17] used first derivative to detect the changes of "red edge" of rice and study the types of crop. With the spectral resolution continuously improving and instrument developing in recent years, it presents enormous potential of using derivative spectroscopy for remote sensing applications. But utilizing this approach to evaluate soil moisture is rarely reported to different soils.

Based on laboratory measurements of different types of soil, main objectives of this study is to investigate the potential of high resolution reflectance spectra to inverse soil surface moisture, and to evaluate the effects of with four sets of data (a. with prototype reflectance, b, with absorbance, c, with the first-order derivative of reflectance, d, with the first-order of absorbance) to estimate soil surface moisture.

2 MATERIALS AND METHODS

2.1 Preparation of soil samples

To evaluate the effect of soil surface moisture in respect to reflectance, we chose 18 soil samples with signi-ficant contrast difference in color and texture characteristics. 9 soil samples of them were selected to evaluate the correlation between four sets of spectral data and soil surface moisture, and then choose the best band to create the equation for estimation of soil surface moisture, the other 9 soil samples were for the verification purpose. All soil samples were initially air-dried while outside for one week and then passed through a 2-mm sieve. Soil samples were put into metal boxes (ø 10 cm). To produce the profile saturation, two procedures were carried out: a) Complete saturation and b) Let surface moisture disappeared. Prepared soil samples were in this way available to measure their spectral and directional reflectance.

2.2 Spectral reflectance of soil samples

Spectral measurements were perfomed in the laboratory to control irradiant conditions and isolate them from other disruptive external conditions. Bidirectional spectral reflectance data over the 350 nm to 2500 nm wavelength region were acquired with ASD Pro FR Portable Spectroradiometer. The Spectroradiometer was used in the laboratory with sampling interval: 1.4 nm for 350—1000 nm, 2 nm for 1000—2500 nm with a sensor field of view 8°. It was positioned vertically at a distance of 40 cm over the soil sample. The light source, a 600W halogen lamp, with almost collimated rays for the sample area was positioned 70cm from the sample container. The zenith angle of the light source was 15°. The lamp was connected to a regulation to avoid possible variation of electrical power input. Where the soil samples and a white Spectralon panel (30 cm × 30 cm) (Labsphere, Inc., North Sutton, NH, USA) were measured under the same illumination and observation conditions.

2.3 Soil measurements

In the whole measuring process, the soil samples were kept undisturbed, and the observation was under the controlled conditions. For soil samples, the mainly varied variables are soil moisture. Followed time passed, the soils moisture decreased, and we measured reflectance of these soil samples, and then instantly measured their weight. Soil moisture was measured with gravimetry. Soil color is easily to detect with the chart of Musell, and the chemical and the analysis laboratory of soil analyzed physical characteristics of soils. The results of 18 soils of those soils are shown in Table 1 and Table 2. In Table 1, these soils were served to create the correlation between spectra and soil moisture and create estimation equation. And the soils of Table 2 were served to validate the estimation equation.

Table 1 Characteristics of 9 soils used to create estimation equation

Soil sample	Org. Matter/%	$CaCO_3$/%	Fe_2O_3/%	Munsell Color	Sand/%	Clay/%	Silt/%
Soil 1	1.41	0	0.93	10YR 3/3	39	31	30
Soil 4	2.21	11.97	1.49	7,5 YR 3/4	29	39	32
Soil 7	1.68	21	0.66	10YR 3/4	44	31	25
Soil 10	1.17	6.93	0.87	10YR 4/4	29	46	25
Soil 13	0.87	3.36	0.66	10YR 5/4	63	22	15
Soil 16	1.51	3.78	2.06	10YR 4/6	37	27	36
Soil 18	0.74	1.89	1.09	10YR 7/3	46	24	30
Soil 20	1.84	25.2	0.39	10YR 4/2	16	62	22

Soil 22	1.24	26.67	0.43	2,5 Y 7/1	16	58	26

Table 2 Characteristics of 9 soils used to verify estimation equation

Soil sample	Org. Matter/ %	$CaCO_3$/ %	Fe_2O_3/ %	Munsell Color	Sand/ %	Clay/ %	Silt/ %
Soil 2	1.44	2.1	0.8	10YR 2/3	37	37	26
Soil 5	1.07	3.15	0.94	10YR 6/3	45	8	27
Soil 8	1.78	13.44	0.7	10 YR 2/3	37	38	25
Soil 11	1.01	8.82	0.72	10YR 4/4	25	38	37
Soil 14	0.97	15.96	0.54	10 YR 6/3	37	42	21
Soil 17	0.8	2.31	1.75	7,5 YR 4/6	54	20	26
Soil 19	0.64	0	0.87	7,5 YR 4/3	49	28	23
Soil 21	1.71	22.1	0.49	10YR 5/2	15	62	23
Soil 23	2.78	23.94	0.31	2,5 Y 5/1	19	51	30

2.4 Description of approaches

In this study, four sets of data (Prototype reflectance, Absorbance, the first-order derivative of reflectance, the first-order derivative of absorbance) were used to evaluate the spectral effect of soil surface moisture and correlation between soil surface moisture and soil spectral data. Here the prototype reflectance was defined as the ratio of reflected power to incident power. The absorbance was defined as $\log(1/R)$ (R is prototype reflectance). The first derivative reflectance was calculated with the finite approximation approach. The first derivative reflectance is calculated by followed Equation (1).

$$\frac{dR}{d\lambda}\bigg| \approx \frac{R\left(\lambda_{i+2}\right) - R\left(\lambda_i\right)}{\lambda_{i+2} - \lambda_i} \tag{1}$$

Where $R\left(\lambda_{i+2}\right)$ and $R\left(\lambda_i\right)$ were reflectance at wavelength λ_{i+2}, λ_i individually. λ_{i+2}, λ_i were the wavelength of band $i+2$ and band i individually.

The first derivative of absorbance was calculated by Equation (2):

$$\frac{d(\log(1/R))}{d\lambda}\bigg| \approx \frac{\log\left(R\left(\lambda_{i+2}\right)\right) - \log\left(R\left(\lambda_i\right)\right)}{\lambda_{i+2} - \lambda_i} \tag{2}$$

In order to analyze the spectral effect of soil surface moisture, prototype reflectance, absorbance, the first-order derivative of reflectance, and the first-order derivative of absorbance were used to create the correlation between soil moisture and soil reflectance at the spectral dimension. Then we chose the spectral data of waveband with great coefficient of determination (ρ^2, square of correlation coefficient) as the variable to estimate soil surface moisture. Finally, we validated the estimation equation with spectra data of other soils.

3 DATA ANALYSIS AND RESULT

3.1 Prototype reflectance, absorbance, the first-order derivative of reflectance and the first-order derivative of soil samples

This part tries to evaluate the relationship between spectral information and soil reflectance moisture. Fig. 1 shows the reflectance, the absorbance and the derivative spectra of reflectance and absorbance for different types of soil. Fig. 2 shows the reflectance, the absorbance and the derivative spectra of reflectance and absorbance for the same soil at different moisture levels. From Fig. 1(a) we can see that with soil color varied from light to dark, the spectral curves of soil varied from high to low about the whole curve. It looks like the spectral effect of soil surface moisture varied from high to low. So it shows the difficulty with prototype reflectance to forecast soil surface moisture of different soil types. Their absorbance curves (See Fig. 1(c) and Fig. 2(c)) are little different in the water absorption band 1400 nm and 1900 nm, but this is not sufficient to distinguish the spectral effect of soil color and soil surface moisture. After the first-order derivative processing, the difference of the first-order derivative of reflectance and absorbance between soil types is not obvious after 1250 nm (See Fig. 1(b) and Fig. 1(d)). But the difference of the effect of soil moisture can be seen in the Fig. 2(b) and Fig. 2(d) after 1250 nm. In

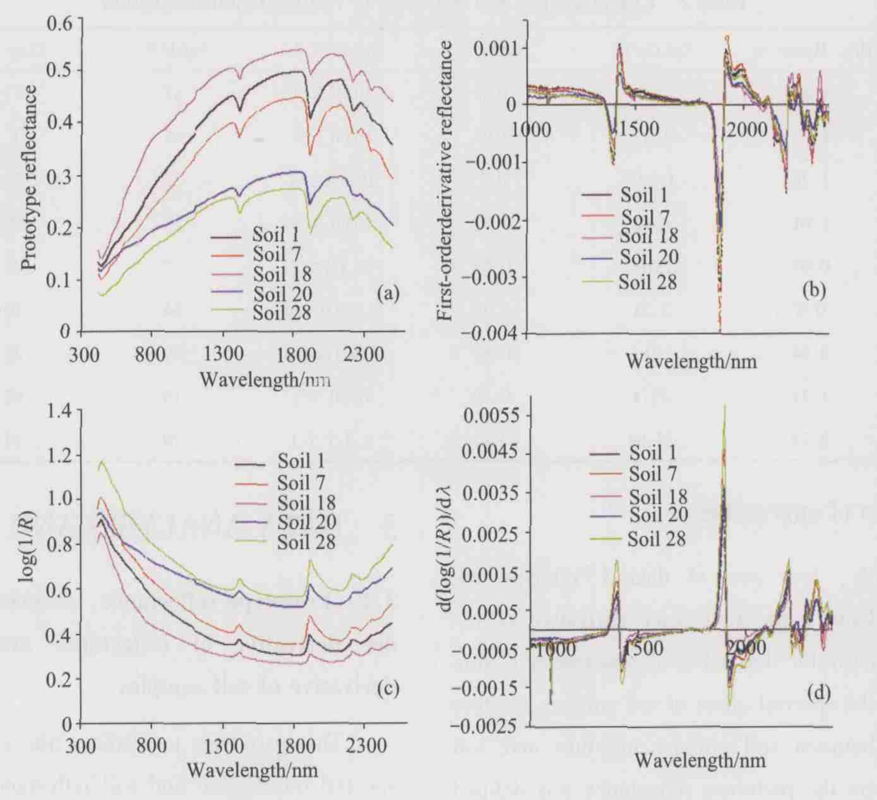

Fig. 1 The prototype reflectance, absorbance and the derivative spectra of reflectance and absorbance for different soils moisture varied with wavelength

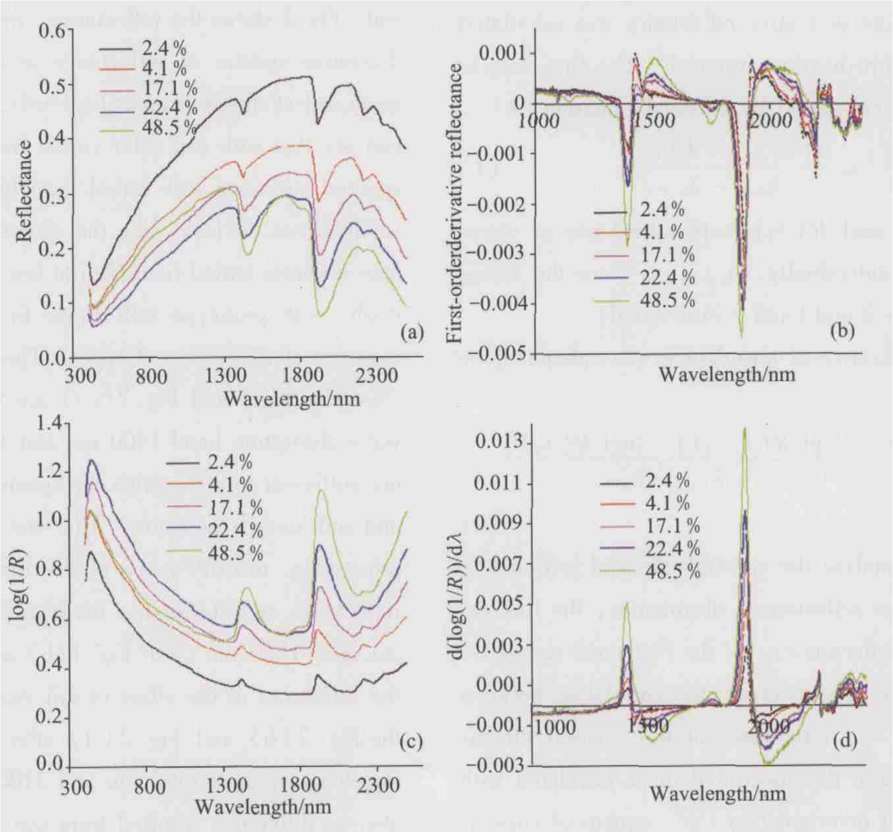

Fig. 2 The reflectance, the absorbance and the derivative spectra of reflectance and absorbance for different soils varied with wavelength

some wavelength ranges 1500 nm and 2100 nm, they have

the obvious difference resulted from soil moisture. It demonstrates the first-order derivative of reflectance and absorbance is sensitive to soil moisture and insensitive to soil color in some waveband.

3.2 Analysis of correlation

From Fig. 2, we can see that it is difficult to evaluate which kind of data is more suitable to estimate soil moisture. So we use ten different soils (50 soil moistures) to calculate correlation between soil surface moisture and soil spectra (Including prototype reflectance, absorbance, the first order derivatives of reflectance and absorbance). Fig. 3 shows the square correlation between soil moisture and R (reflectance), $\log(1/R)$ (Absorbance), $dR/d\lambda$ (the first derivative of reflectance), $d(\log(1/R))/d\lambda$ (the first derivative of absorbance) varied with wavelength. We can see for prototype reflectance and absorbance they do not have very high correlation squares, and absorption can improve the power of reflectance to estimate soil moisture. So it demonstrates that with prototype reflectance and absorbance to estimate moisture of different soils is difficult to get good results. The result coincides with W. R. Whalley. Even to the same soil, around the 1450 nm and 1940 nm, there is good correlation, but they are located in the outside of atmosphere windows, in the practical application it is difficult to apply.

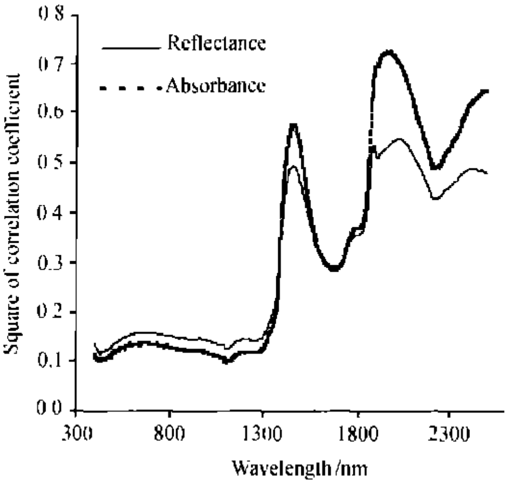

Fig 3 The correlation between soil moisture and reflectance, absorbance

Fig. 4 shows the relationship (square of correlation coefficient, ρ^2) between soil moisture and the first-order derivative of reflectance and absorbance. In the range of 400 nm to 1300 nm, there are no obvious correlation between the first-order derivative of reflectance and absorbance. But after 1300 nm, we can see there are many wavebands with the better square of correlation coefficient. It demonstrates that derivatives spectra in some wavebands are sensitive to soil moisture derivative. We chose the wavelength with best square of correlation coefficient ρ^2 (With reflectance, absorbance and the first-order derivative of reflectance and absorbance) to create liner regression equation. For prototype reflectance (R), the best band is 2022 nm, for $\log(1/R)$, the best band is 1962 nm. Both 2022 nm and 1962 nm are located nearby water absorption of atmosphere, and the correlation is not very well. But for the first-order derivative of reflectance and absorbance, they have the higher square of correlation coefficient, and the best band is the same, 1844 nm. Then, we used those wavebands to create the estimation equation individually. Fig. 5 shows the regression equation. Although we chose the best waveband with square of correlation, the relationship between soil surface moisture and prototype reflectance is not linear, so we created a logarithmic equation to forecast soil moisture.

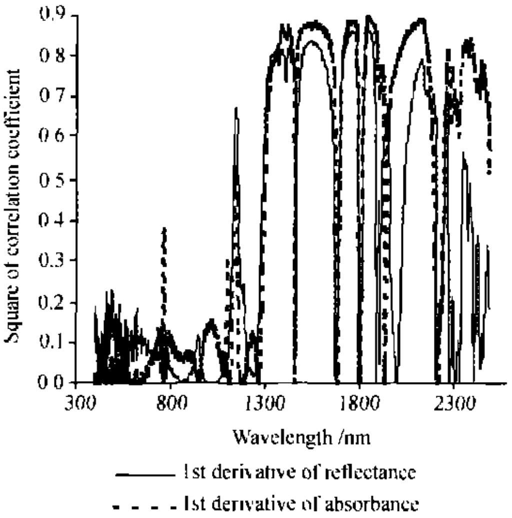

Fig 4 The correlation between soil moisture and reflectance, absorbance

3.3 Evaluation of the estimation equation

Frequently, the experiential forecasting formula is always applied under some certain conditions. In order to validate the precision of estimation equation, we used the

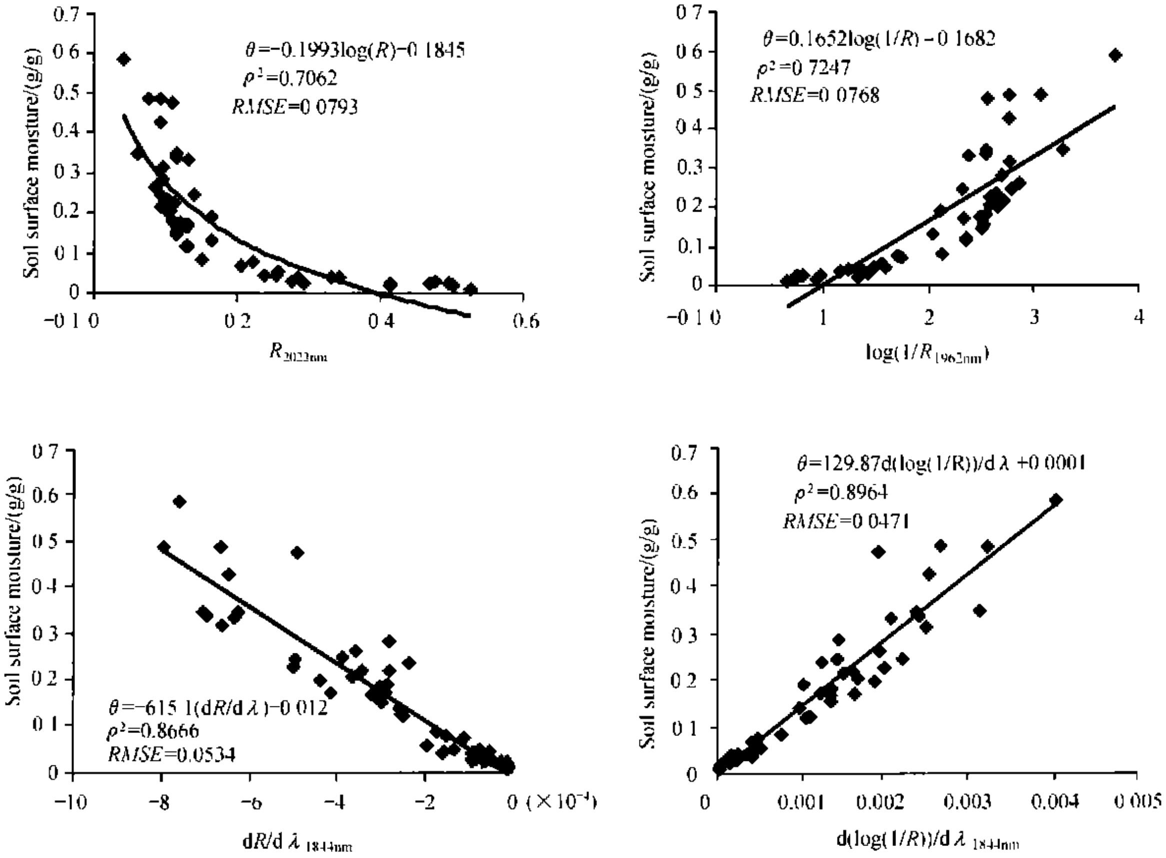

Fig. 5 Creation of estimating equation

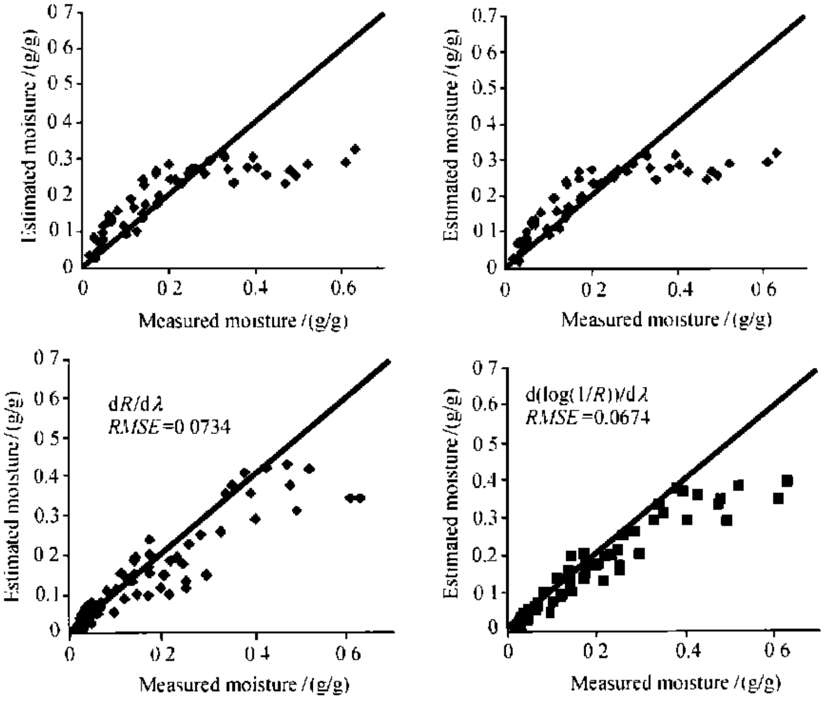

Fig. 6 Evaluation of forecasting equation

moisture of another 9 different soils (65 soil moisture) to verify the precision of estimation equation. Fig. 6 shows soil moisture of measured and estimated by forecasting with four spectral data. We can see, with the prototype reflectance to estimate soil moisture it showed much deviation between measured moisture and estimated moisture, the absolute moisture *RMSE* is 11.79%. With absorbance to estimate soil moisture, the deviation between measured moisture and estimated moisture partly dimini-shed, and the absolute moisture *RMSE* is 9.53%. And after derivative processing, the deviation between measured and estimated moisture are decreased, and the absolute moisture *RMSE* is 7.34%. With the first order derivative of absorbance to estimate soil moisture, the result is the best: the absolute moisture of *RMSE* can get to 6.74%. Thus, the result demonstrated that absorbance is better than prototype reflectance to estimate soil moisture. And the derivative of reflectance can well be applied to estimate soil moisture of different soils. And the first-order derivative absorbance can improve the capability both reflectance and derivative reflectance. The first-order derivative of absorbance has the best effect of estimation in the four methods for different type soils. To the first derivative of logarithmic reflectance, when soil water is not high, it' s very good to estimate soil moisture, the result estimated less than measured moisture. Because when soil moisture is higher than field water content, reflectance will show other appearance[18], here we don' t mention it. But this approach can be applied into different soil types. So it possesses great potential in estimating soil surface moisture in a large region.

4 CONCLUSION

In the optical remote sensing, one of the major problems for estimating soil moisture from reflectance is each soil exhibit a unique response, and it is very difficult to accurately estimate soil surface moisture for different soil types with prototype reflectance and absorbance. The technique of derivatives tackles many of the problems of quantitative analysis in analysis spectroscopy. Application of derivative spectra can decrease the information of background and facilitate the location of critical wavelengths. The paper used raw reflectance, absorbance, the first derivative of reflectance, and the first derivative of absorbance to create correlation between soil moisture and soil spectral data. We found that for different soils it has no obviously correlation between soil surface moisture and prototype reflectance and absorbance, but absorbance can has higher correlation than reflectance. The first-order derivative of reflectance and the first-order derivative of absorbance have the obvious correlation in some certain narrow wavebands; the first-order derivative of absorbance reflectance has more obvious correlation than the first-order derivative of reflectance. We choose these bands with highest square of correlation coefficient to creat liner regression forecasting equation. Another 9 soil samples were used to verify the precision of estimation equation. Results showed that the first-order derivative of absorbance possess the capability to estimate soil surface moisture of the four types data. It shows the great potential in estimating soil surface moisture and other soil characteristics in a large region.

References

[1] Ahuja L R, Wendroth O, Nielsen D R. Relationship between Initial Drainage of Surface Soil and Average Profile Saturated Conductivity [J]. *Soil Sci. Soc. Am. J.*, 1993, **57**: 19—25.

[2] Chepil W S. Influence of Moisture on Erodibility of Soil by Wind [J]. *Soil Sci. Soc. Am. Proc.*, 1956, **20**: 288—292.

[3] Ångström, A. The Albedo of Various Surfaces of Ground [J]. *Geografiska Ann.*, 1925, **7**: 323—327.

[4] Curcio J A, Petty C C. The Near Infrared Absorption Spectwm of Liquid Water [J]. *J. Opt. Soc. Amer.*, 1951, **41**: 302—304.

[5] Bowers S A, Hanks R J. Reflection of Radiant Energy from Soil, Soil Science [J]. 1965, **100**: 130—138.

[6] Stoner E R, Baumgardner M F. Characteristics Variations in Reflectance of Surface Soils [J]. *Soil Sci. Soc. Am. J.*, 1981, **45**: 1161—1165.

[7] Bowers S A, Smith S J. Spectrophotometric Determination of Soil Water Content [J]. *Soil Sci. Soc. Amer. Proc.*, 1972, **36**: 978—980.

[8] Dalal R C, Henry R J. Simultaneous Determination of Moisture, Organic Carbon, and Total Nitrogen by Infrared Reflectance Spectrometry [J]. *Soil Sci. Soc. Am. J.*, 1986, **50**: 120—123.

[9] Hatanaka T, Nishimune A, Nira R *et al*. Estimation of Available Moisture Holding Capacity of Upland Soils Using Landsat TM Data [J]. *Soil Sci. Plant Nutr.*, 1995, **41**: 577—586.

[10] Montgomery, O L. An Investigation of the Relationship between Spectral Reflectance and the Chemical, Physical, and Genetic

Characteristics of Soils, PhD. Thesis, Purdue University. West Lafayette, Indiana. 1976.

[11] Simmons E L. Relation of the Diffuse Reflectance Remission Function to the Fundamental Optical Parameters [J]. *Optica Acta*, 1972, **19**: 845—851.

[12] Baumgardner M F, Silva L F, Biehl L L, *et al*. Reflectance Properties of Soils [J]. *Adv. Agron*. 1985, **38**: 1—44.

[13] Whalley W R, Leeds-Happison P B, Bowman G E. Estimation of Soil Moisture Using Near Infrared Reflectance [J]. *Hydrological processes*, 1991, **5**: 321—327.

[14] Chen Z, Curran P, Hansom J. Derivative Reflectance Spectroscopy to Estimate Suspended Sediment Concentration [J]. *Remote Sensing of Environment*, 1992, **40**: 67—77.

[15] Gong P, Pu R L, Yu B. Conifer Species Recognition: an Rxploratory Analysis of in Situ Hyperspectral Data [J]. *Remote Sensing of Environment*, 1997, **62**: 189—200.

[16] Gong P, Pu R L, Miller J R. Correlating Leaf Area Index of Ponderosa Pine with Hyperspectral CASI Data [J]. *Can. J. Remote Sens*., 1992, **18**(4): 275—292.

[17] Xiang Y Q, Liu W D, Zheng L F, *et al*. Crop Type Classification with Hyperspectral Technique [J]. *SPIE Proceedings*, 1998, **3502**: 124—128.

[18] Liu W D, Baret F, Gu X F, *et al*. Relating Soil Moisture to Reflectance [J]. *Remote Sensing of Environment*, 2002, **81**(2): 238—246.

应用高光谱遥感数据估算土壤表层水分的研究

刘伟东[1,2,3], F. Baret[2], 张 兵[3], 郑兰芬[3], 童庆禧[3]

(1. 中国气象局 北京城市气象研究所, 北京 100089;

2. INRA, Bioclimatologie, Domaine Sanit-Paul, Site Agroparc, 84914 Avignon, Cédex 9, France;

3. 中国科学院遥感应用研究所遥感信息科学开放实验室, 北京 100101)

摘 要: 土壤水分是土壤的重要组成部分, 它在陆地表层和大气之间的物质和能量交换方面扮演着重要角色, 寻求快速而准确的方法估算土壤水分具有重要意义。通常, 从可见光—近红外对土壤表层水分的估计多是建立在土壤水分与反射率的关系之上的。而在土壤水分含量不高时, 土壤水分的增加使土壤光谱反射率在整个波长范围内降低, 尤其在 760 nm, 970 nm, 1190 nm, 1450 nm, 1940 nm 和 2950 nm 等水分吸收波段, 而在土壤水分含量较高时, 土壤水分的增加会使土壤光谱反射率在某些光谱波段升高。而土壤水分的估计往往是基于土壤水分与土壤水分吸收波段的吸收强度之间的线性关系上, 虽然这些经验的方法对于估算某些土壤的表层水分含量是有效的, 但这些关系应用于其它条件(如不同种类土壤、土壤湿度变化范围很大的情况)时却面临很多困难, 这与土壤的光谱反射率是由土壤的组成成分(土壤水分、有机质、氧化铁和粘土矿物等)的含量和它们在土壤中的分布密切相关。

微分技术处理“连续”的光谱是遥感中常用的数学方法, 微分技术能部分消除低频光谱成分的影响。现在微分光谱已广泛地应用于研究植被的生物物理参数、矿物和有机质等。然而利用微分光谱对土壤水分反演的研究却鲜见报道。本文通过对实验室中多种不同类型的土壤进行光谱与土壤表层水分含量进行观测, 探讨了通过土壤反射率与微分光谱对土壤表层水分的反演方法。

4 种类型的土壤光谱数据(反射率(R), 反射率倒数的对数($\log(1/R)$), 反射率的一阶微分光谱($\mathrm{d}R/\mathrm{d}\lambda$), 反射率倒数的对数的一阶微分光谱($\mathrm{d}(\log(1/R))/\mathrm{d}\lambda$))与土壤表层水分之间的关系在本文中得到分析, R 与 $\log(1/R)$ 对于不同土壤类型与土壤表层水分都很敏感, 说明通过 R 与 $\log(1/R)$ 反演土壤表层水分受土壤类型的影响很大, 而 $\mathrm{d}R/\mathrm{d}\lambda$, $\mathrm{d}(\log(1/R))/\mathrm{d}\lambda$) 对土壤类型却不敏感, 对土壤表层水分较为敏感, 说明 $\mathrm{d}R/\mathrm{d}\lambda$ 和 $\mathrm{d}(\log(1/R))/\mathrm{d}\lambda$) 对于反演不同类型土壤具有很大的潜力, 微分光谱与土壤水分在某些波段具有显著的相关性。通过随机对 9 种土壤(各具有 4 个土壤水分)的数据建立反演土壤水分的模型, 并其他 9 种土壤(各具有 4 个土壤水分)的数据进行验证模型, 结果表明, $\mathrm{d}R/\mathrm{d}\lambda$ 和 $\mathrm{d}(\log(1/R))/\mathrm{d}\lambda$) 能够显著提高 R 与 $\log(1/R)$ 对于不同类型土壤表层水分的反演精度, 由于吸收过程是非线性的, 在四种类型的土壤光谱数据中, 总体来说, $\mathrm{d}(\log(1/R))/\mathrm{d}\lambda$) 具有最好的能力预测不同类型土壤的表层水分含量。

关键词: 土壤水分; 高光谱; 导数光谱; 反射率