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Predicting Surface Roughness and Moisture of Bare Soils Using Multi-band Spectral Reflectance Under Field Conditions

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Abstract: Soil surface roughness, denoted by the root mean square height (RMSH), and soil moisture (SM) are critical factors that affect the accuracy of quantitative remote sensing research due to their combined influence on spectral reflectance (SR). In regards to this issue, three SM levels and four RMSH levels were artificially designed in this study; a total of 12 plots was used, each plot had a size of 3 m × 3 m. Eight spectral observations were conducted from 14 to 30 October 2017 to investigate the correlation between RMSH, SM, and SR. On this basis, 6 commonly used bands of optical satellite sensors were selected in this study, which are red (675 nm), green (555 nm), blue (485 nm), near infrared (845 nm), shortwave infrared 1 (1600 nm), and shortwave infrared 2 (2200 nm). A negative correlation was found between SR and RMSH, and between SR and SM. The bands with higher coefficient of determination R^2 values were selected for stepwise multiple nonlinear regression analysis. Four characterized bands (i.e., blue, green, near infrared, and shortwave infrared 2) were chosen as the independent variables to estimate SM with R^2 and root mean square error (*RMSE*) values equal to 0.62 and 2.6%, respectively. Similarly, the four bands (green, red, near infrared, and shortwave infrared 1) were used to estimate RMSH with R^2 and *RMSE* values equal to 0.48 and 0.69 cm, respectively. These results indicate that the method used is not only suitable for estimating SM but can also be extended to the prediction of RMSH. Finally, the evaluation approach presented in this paper highly restores the real situation of the natural farmland surface on the one hand, and obtains high precision values of SM and RMSH on the other. The method can be further applied to the prediction of farmland SM and RMSH based on satellite and unmanned aerial vehicle (UAV) optical imagery.
Keywords: soil surface roughness; soil moisture; spectral reflectance; field conditions; stepwise multiple nonlinear regression

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1 Introduction

Soil moisture (SM) plays a vital role in governing water and energy cycles of the land-atmosphere interface; moreover, an accurate estimation of large-scale SM plays a crucial role in crop growth, prediction of flood and drought events, hydrology, and the global water cycle. Additionally, soil surface roughness, indicated by root mean square height (RMSH), is a key element in the hydrological and erosive behavior of soils (Helming et al., 1998) and plays an important role in many processes, such as infiltration, run-off, detachment of soil

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due to water or wind, gas exchange, evaporation, and heat flux (Huang and Bradford, 1992). But the traditional methods of acquiring soil surface roughness and soil moisture are resource heavy and time-consuming, there is still a lack of means to obtain their space-time distribution information.

Satellite remote sensing measures and monitors space-time changes in SM and has the potential to provide data at a fine temporal resolution. Much of the work into quantifying SM through remote sensing approaches has been focused on soil reflectance; it allows to obtain quantitative information about several soil parameters based on high-resolution spectra in relatively short periods (Irons et al., 1989). To describe correlations between soil reflectance and soil properties, regression models are built by mainly using laboratory spectra and, to a lesser extent, spectra obtained in a field or extracted from images (Stevens, 2008).

However, the estimated accuracy of SM is limited by the combined effect of SM and RMSH on spectral reflectivity. Therefore, a great number of researches have been effectuated to explain the mechanisms of the influence of RMSH on spectral reflectance (SR); most of them were conducted using laboratory-based measurements (Croft et al., 2012a; Dor et al., 2015). It is necessary to broaden the application of those techniques for field use so that they can be employed in agricultural activities (Wu et al., 2002). The results from laboratory reflectance measurements only consider the interaction between soil particles; unfortunately, the effects of the clods and randomly distributed aggregates on the farmland surface are not taken into consideration (Oguntunde et al., 2006; Piekarczyk et al., 2016), thus limiting the reliability of SM estimation in a natural farmland. In addition, laboratory spectral reflectance is free of atmospheric vapor influence, so it should not be used for the interpretation of satellite or airborne image data. For proper extension of spectral reflectance for soil surface assessments, the connection between spectral reflectance and soil parameters under field conditions should be inspected.

The spectral reflectance of bare soils is strongly dependent on SM and RMSH (Bowers and Smith, 1972). Generally, an increase in SM causes a decrease in SR. Under the circumstances of SM being lower than the hygroscopic capacity, changing in soil reflectance resulted by the decrease of SM is not, or only slightly noticed. The soil reflectance drops significantly if the SM level increases from the hygroscopic capacity to the field capacity; a further increase in the SM to the full saturation causes no, or only a slight, change in the soil reflectance. When the SM is greater than the field capacity, water films form on the surface of the bare soil, which causes an increase in the soil reflectance (Music and Pelletier, 1986; Cierniewski, 1993; Cierniewski et al., 2015). A reduction in the reflected energy of wet soils is due to a decrease in the relative refractive index, which leads to light scattering in the direction of the incident radiation and the absorption of more incident photons (Croft et al., 2014).

Besides SM, the surface roughness of the soil also has an important influence on SR, especially under dry conditions. The most commonly used techniques for measuring soil roughness are laser scanner, photogrammetry, and mechanic profilometer (Bryant et al., 2007; Alvarez-Mozos et al., 2009; Marzahn and Ludwig, 2009). Here, the root mean square height (RMSH) is used to describe the roughness of bare soils. Strong correlations have been found between optical directional reflectance factors and RMSH for laboratory-produced soil states under controlled conditions (Anderson and Kuhn, 2008; Croft et al., 2009; 2012b). However, under field conditions, the interaction between other soil properties may perturb the signal from RMSH (Mouazen et al., 2006). Potter et al. (1987) observed that soil reflectance decreased when RMSH increased in a fine-loamy soil, which is possibly attributed to shadows cast on the surface. Matthias et al. (2000) obtained a similar finding on Gila fine sandy loam and Pima clay loam. The RMSH of soils depends on the agricultural treatments and climate; its value is highest after plowing and progressively decreases with rainfall (Karunatilake and Es, 2002). Furthermore, it is difficult for indoor measurements to simulate the changes of RMSH, which constricts the studies that focus on the effect of RMSH on reflectivity.

To improve the estimated accuracy of SM from the SR of bare soils under natural conditions, the effect of both SM and RMSH on the SR of bare soils are investigated here. For achieving this goal, a ground-based spectral observation experiments with various SM and RMSH levels was carried out, which help to comprehend the relationships between SR, SM, and RMSH. On this basis, a high precision method for estimating SM and RMSH from SR is developed and analyzed in this study. This method will serve for the SM estimation with higher accuracy under different RMSH conditions, and the retrieval of SM and RMSH at a satellite remote sensing scale.

2 Data and Method

2.1 Experimental area

The experiment was carried out on a farmland (43°52′59″N, 125°24′05″E) located in Changchun City, Jilin Province, China. The soil type in this area is chernozem, with a salt content of 234 mg/kg, an organic carbon content of 1.17%, and total nitrogen, phosphorus, and potassium contents of 809.26 mg/kg, 395.63 mg/kg and 22.26 mg/g, respectively. In order to study the influence of SM and RMSH on the soil SR, a 108 m^2 area of open farmland was selected as the experimental region. This region was divided into 12 sub-regions, each with a 3 m × 3 m area (Fig. 1). Prior to experiment designing, many field surveys were conducted in Northeast China, and the fluctuation range of the soil surface roughness under field conditions was measured and calculated. The 12 experimental sub-regions were set up by imitating farming activities. The designed ranges of SM and RMSH were consistent with the results obtained in field surveys; indeed, the SM values were not larger than theoretical field capacity values (Deng et al., 2004).

As shown in Fig. 1, four different RMSH levels were set up by artificial plowing and compaction. RMSH1 and RMSH2 were the smallest areas that were compacted twice and once after plowing, respectively, while RMSH3 was the special one in which the biggest clods must be broken up after plowing, and RMSH4 was the biggest one that was only plowed (it was not compacted). Although the three plots of one SM level have the same surface roughness level, the RMSH of each plot was measured instead of adopting a preset uniform value to avoid errors caused by the manual operation.

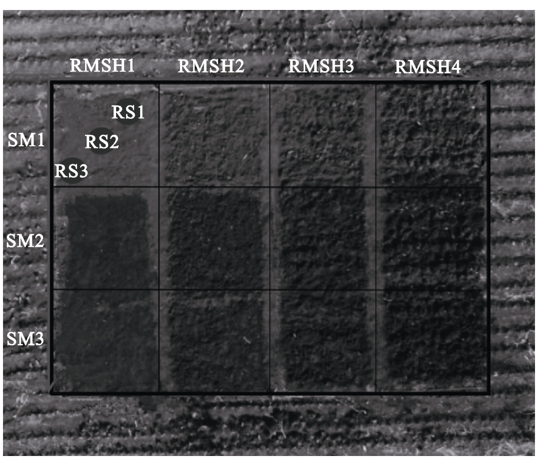

Fig. 1 Layout of the experimental area. SR1, SR2, SR3 are spectral reflectance measured areas in each sub-regions. RMSH1, RMSH2, RMSH3, RMSH4 are four surface roughness levels, SM1, SM2, SM3 are three soil moisture levels

Moreover, three different simulated rainfalls were applied to the sub-regions. SM1 had the lowest rainfall levels, which mimics the natural state, SM3 had the highest rainfall level, which was adequate to produce a little water film, and SM2 had a medium rainfall level and consisted of half the rainfall level of SM3. Water was sprayed with a portable spray bottle, and the water flow rate was controlled so that the water was evenly and slowly dropped onto the soil to minimize soil surface disturbance.

2.2 Outdoor measurements

In this experiment, 8 observations were carried out throughout the study period; moreover, 96 groups of soil SR and the corresponding SM and RMSH values, in real time, were collected (Table 1). The RMSH and SM values ranged between 0.56–5.08 cm and 7.4%–28.2%, respectively. Unlike the RMSH values that slightly changed among the observations, the SM values noticeably varied. The SM increased after plowing and compaction on October 14, 2017 because the soil was turned over, which lead to the presence of moist soil on the top. Watering was done on the 17th and 30th of October to artificially change the soil moisture content, which obviously lead to SM increase. According to the range of the soil parameters, RMSH was divided into four levels, which are RMSH1 ≤ 1.5 cm, 1.5 cm < RMSH2 ≤ 2.5 cm, 2.5 cm < RMSH3 ≤ 3.5 cm, and RMSH4 > 3.5 cm. Due to the fluctuating SM values, it was divided into four levels, which are SM1 ≤ 10%, 10% < SM2 ≤ 15%, 15% < SM3 ≤ 20%, and SM4 > 20%.

2.2.1 Spectral reflectance measurements of bare soils

The FieldSpec 4 spectroradiometer was used to measure the reflectance of the soil surface in outdoor conditions (American ASD Inc.). The experiment time was chosen between 11:00 and 13:00 to ensure a suitable solar elevation angle. The measurement locations are indicated by SR1, SR2, and SR3 in each sub-region (circles in

Table 1 Soil spectral reflectance, soil surface roughness, and soil moisture data

Date	Soil spectral reflectance	Value range of soil surface roughness (cm)	Value range of soil moisture (%)
2017-10-14	36	0.65–4.27	16.2–22.2
2017-10-16	36	0.65–4.51	13.3–17.4
2017-10-17	72	0.56–4.31	11.4–27.7
2017-10-19	36	0.70–4.35	9.4–22.2
2017-10-21	36	0.62–4.60	9.2–18.0
2017-10-23	36	0.62–4.60	9.2–18.0
2017-10-25	36	0.66–5.08	7.4–14.9
2017-10-30	36	0.69–4.88	7.7–28.2

Fig. 1). During the experiment, the 25° optical fiber probe was perpendicular to the soil surface with a height of 100 cm. The output spectral reflectance was obtained by automatically averaging the 10 original scanned spectral reflectance curves, and each sub-region was measured 3 times. The measurements were accepted if the mean relative difference was less than 1%, otherwise, the measurements were repeated.

Due to the instrument's stability and environmental factors, soil spectral reflectance data obtained in outdoor farmland require a series of preprocessing (Cierniewski et al., 2017). Mean reflectance from the three measurements was calculated, spliced, and smoothed. A set of spectral reflectance curves in figure 2 with different soil parameters were selected to study the variation of SR and SM, as well as SR and RMSH. The spectral reflectance curve is a common way to show how reflectivity varies with soil parameters.

It is clear that the reflectance of the soil spectra shows certain fluctuations under different conditions, but the overall shape and trend are generally the same (Fig. 2). As SM and RMSH increase, the reflectance curve moves downward. Significant reduction in SR with increasing SM and RMSH was observed ($P <$ 0.01). According to the experimental data (Fig. 2), about an 80% increase in SR was associated with a decrease in RMSH from 4.31 to 0.56 cm, and a 40% increase in SR was associated with a decrease in SM from 27.7% to 11.4%.

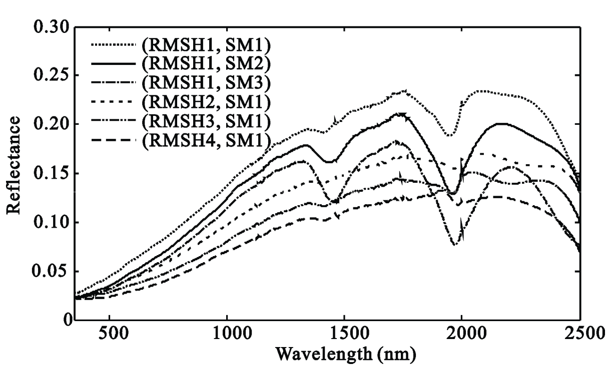

Fig. 2 Spectral reflectance of the soil surface with different moisture and roughness levels

2.2.2 Soil parameters measurements of bare soils

The RMSH was measured by a profiler. In each sub-region, the profiler was placed vertically on the soil surface; a picture was taken with a camera. It must be noted that the profiler was placed on a straight line and covered the entire sub-region. For accurate RMSH readings, the measured length was 40–200 times more than the surface correlation length. The profiler images were preprocessed and the values of RMSH were calculated based on the fractal correlation function (Li et al., 2012; Zheng et al., 2013). In addition, the above steps were repeated three times to strictly limit the error of RMSH readings within 10% (Taconet and Ciarletti, 2007).

The common oven drying method was used to obtain the water contents of the soil samples. The surface 0–5 cm soil samples around the SR1, SR2, and SR3 circles (Fig. 1) in each subplot were collected by a cutting ring. Triplicate soil samples were taken from each sub-region. The soil moisture (SM) was calculated according to Equation (1).

$$SM = \frac{m_1 - m_2}{m_2} \times 100\% \tag{1}$$

where m_1 and m_2 (g) are the soil masses before and after drying, respectively.

It is worth noting that SM and RMSH change frequently in time and space, which are influenced by factors such as wind, rainfall, and human farming activities. Therefore, soil parameters were acquired within one hour after the surface reflectance measurement.

2.3 Characteristic bands selection

In order to explore the link between the soil spectral reflectance and the soil parameters, and to determine the characteristic bands of SM and RMSH, correlation analysis was used in this study, which was also used in other studies (e.g., Music and Pelletier, 1986; Bogel et al., 2016). Considering that the estimation model is further applied to optical satellite imagery to estimate RMSH and SM under field conditions, we summarized the spectral range of each band of existing optical satellite sensors (Qi et al., 2018).

It can be seen that the wavelength ranges of commonly used optical sensors are similar (Table 2). The determination of these wavelength ranges is the result of long-term theoretical and applied research. Combining the above results with our study objectives, six characterized bands were selected according to the center wavelength of common optical satellites, which are B (blue band, 485 nm), G (green band, 555 nm), R (red band, 675 nm), NIR (near infrared band, 845 nm), SWIR1 (shortwave infrared 1 band, 1600 nm), and SWIR2 (shortwave infrared 2 band, 2200 nm). Subsequently, correlation analysis of reflectivity and soil parameters were made.

To analyze the contribution of RMSH and SM to SR, it is necessary to determine the correlation coefficients; the number of variables and system dimensions will be reduced accordingly. In general, variables with different dimensions cannot be directly compared; indeed, it is difficult to judge the effect of independent variables with different dimensions on the dependent variables using regression coefficients (Dotto et al., 2017). Therefore, the correlation coefficients of standardized data were calculated to find the bands that are greatly related to the soil parameters. This step helped to reduce the negative effects of collinearity and to improve the stability of the multiple nonlinear regression equations. The matrix was calculated by Pearson's correlation coefficient. However, the correlation coefficient is not sufficient to determine whether the variables are correlated; therefore, Pearson's correlation coefficient was coupled to the test of significance.

The correlation coefficients and significance levels between the single-band reflectivity of different bands and the soil parameters were quite high (Table 3), which are consistent with previous conclusions (Liu et al.,

Table 2 The wavelength ranges of commonly used optical sensors (nm)

Bands of sensors	L7-ETM+	L8-OLI	Sentinel-2	GF-1_WFV
B band	450–515	450–515	458–522	450–520
G band	525–605	525–600	544–578	520–590
R band	630–690	630–680	650–680	630–690
NIR band	775–900	845–885	784–900	770–890
SWIR1 band	1550–1750	1560–1660	1565–1655	–
SWIR2 band	2090–2350	2100–2300	2100–2280	–

Notes: ETM+ is Enhanced Thematic Mapper of Landsat 7, OLI is Operational Land Imager of Landsat 8, WFV is wide field of view multispectral sensor of GF-1

Table 3 Pearson's correlation coefficient of standardized soil parameters and single-band reflectivity data

Standardized data	Soil parameters		Single-band reflectivity					
	SM	RMSH	B	G	R	NIR	SWIR1	SWIR2
SM	1.000**	0.108	–0.567**	–0.548**	–0.508**	–0.415**	–0.443**	–0.534**
RMSH	0.108	1.000**	–0.463**	–0.471**	–0.486**	–0.513**	–0.441**	–0.394**
B	–0.567**	–0.463**	1.000**	0.998**	0.990**	0.959**	0.940**	0.939**
G	–0.548**	–0.471**	0.998**	1.000**	0.996**	0.972**	0.955**	0.950**
R	–0.508**	–0.486**	0.990**	0.996**	1.000**	0.987**	0.972**	0.962**
NIR	–0.415**	–0.513**	0.959**	0.972**	0.987**	1.000**	0.986**	0.960**
SWIR1	–0.443**	–0.441**	0.940**	0.955**	0.972**	0.986**	1.000**	0.986**
SWIR2	–0.534**	–0.394**	0.939**	0.950**	0.962**	0.960**	0.986**	1.000**

Notes: * and ** denote significance at the 5% and 1% levels, respectively. SM: soil moisture. RMSH: root mean square height. B, G, R, NIR, SWIR1 and SWIR2 represent blue, green, red, near infrared, shortwave infrared 1 and shortwave infrared 2 bands, respectively.

2002). Moreover, the soil parameters (i.e., RMSH and SM) have a significant influence on SR, which is demonstrated by significant negative correlations. However, there is no obvious correlation between SM and RMSH; they can be separately treated as two independent variables.

2.4 Estimation method of soil moisture and soil surface roughness

Pearson's correlation coefficient clearly indicated that SM and RMSH are negatively correlated with single-band reflectivity (Table 3). Based on those results, the correlation between single-band spectral reflectance and SM under the condition of constant RMSH was analyzed by curve fitting method; the correlation between single-band spectral reflectance and RMSH under the condition of constant SM was also analyzed by curve fitting method. The fitting trend lines of linear, exponential, logarithm, and power forms were used to describe the relationship between them, and the fitting model with the highest coefficient of determination (R^2) was eventually chosen.

The single-band spectral reflectance of bare soil was highly dependent on soil moisture, especially under constant soil surface roughness conditions (Fig. 3). A decrease in soil surface reflectance was observed with increasing soil moisture. Under constant RMSH conditions, single-band reflectance exponentially decreased with increasing SM. The change of SR with SM is therefore expressed by a nonlinear equation, according to the following equation (Liu et al., 2002).

$$SR_i = A_i \times e^{B_i \times SM} \tag{2}$$

where SR_i is the reflectance, SM is the soil moisture, A_i and B_i are regression coefficients, and i is the band (i = B, G, R, NIR, SWIR1, and SWIR2).

The equation obtained in this study through nonlinear regression is consistent with the Beer Law (Deng et al., 2004). Equation (2) gave an expression of the physical mechanisms between SM and SR. Moreover, when the SM is significantly smaller than the field capacity, no smooth water film is formed on the soil surface, and the SM mainly absorbs the incident light. Assuming that the SR of bare soils is known, it is not certain that the SM can be accurately estimated using SR. In this study, the SR of different bands as independent variables was taken to build an SM estimation expression; the estimation of SM from reflectance can be achieved by using multiple nonlinear regression equations according to the above conclusion.

$$SM = a + b_1 \ln SR_1 + b_2 \ln SR_2 + ... + b_n \ln SR_n \tag{3}$$

where a and b_i are multiple regression coefficients.

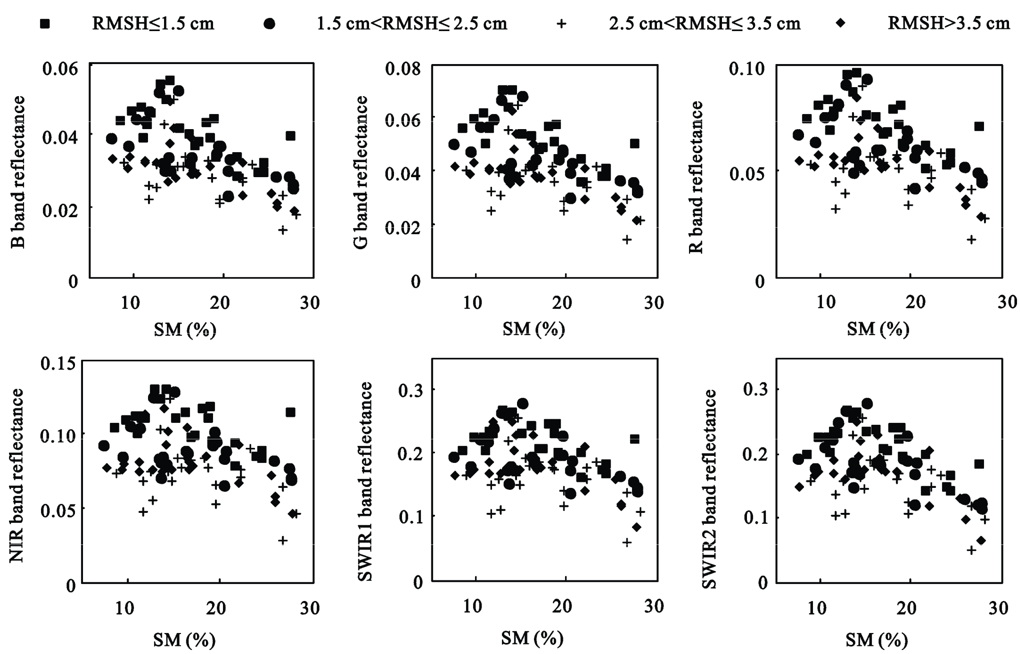

Fig. 3 Single-band SR variation with SM under constant RMSH conditions

The fitting trend line of linear, exponential, logarithm, and power form was also used to describe the correlation between single-band SR and RMSH, and the fitting method with the highest R^2 was eventually adopted. The results in Fig. 4 indicated that RMSH also plays an important role in SR. A reduction in single-band SR logarithmically decreased with the increase of RMSH, which is summarized by Equation (4).

$$SR_i = C_i + D_i \times \ln\left(RMSH\right) \tag{4}$$

where SR_i is the reflectance, $RMSH$ is the soil surface roughness, C_i and D_i are the regression coefficients, and i is the band of reflectance (i = B, G, R, NIR, SWIR1, and SWIR2). When investigating RMSH estimation from reflectance data, the inverse problem must be solved. This corresponds to a potential application of remote sensing for RMSH assessment; this can be part of an assimilation strategy of such data within models describing the effects of soil surface structural characteristics on energy. Like SM, RMSH estimating equation can be expressed as indicated in Equation (5).

$$RMSH = c \times \mathrm{e}^{(d_1 SR_1 + d_2 SR_2 + \ldots + d_n SR_n)} \tag{5}$$

where c and d_i are multiple regression coefficients.

Prediction models of RMSH and SM, using multiple band spectral reflectance, were established. They provide a method for the prediction of soil parameters based on optical spectroscopy and optical imagery.

3 Results

In order to estimate SM and RMSH based on multi-band spectral reflectance, 64 sets of data were selected from 8 sub-regions for testing; additionally, 31 sets of data of the remaining 4 sub-regions were used for verification. By applying the above nonlinear equations (Eqs. (3) and (5)), the multiple nonlinear regression was carried out by stepwise selecting the characteristic bands according to the correlation coefficients and other statistical tests.

One of the main issues with stepwise multiple nonlinear regression is that it searches a large space of possible models. Hence, it is prone to overfitting the data. To solve multicollinearity problems, it is theoretically necessary to calculate the tolerance (TOL) and variance inflation factor (VIF) corresponding to each independent variable. If the VIF and TOL values are less than and greater than 10 and 0.1, respectively, the variable is suitable for multiple nonlinear regression. Nonetheless, the TOL and VIF values of all the independent variables did not meet the empirical standards. Therefore, in the process of selecting variables, the TOL and VIF values were not considered, rather the causal correlation between the independent and dependent variables was further investigated.

This problem can be mitigated if the criterion for adding (or deleting) a variable does not cause significant changes. So, at each stage in the process, and after a

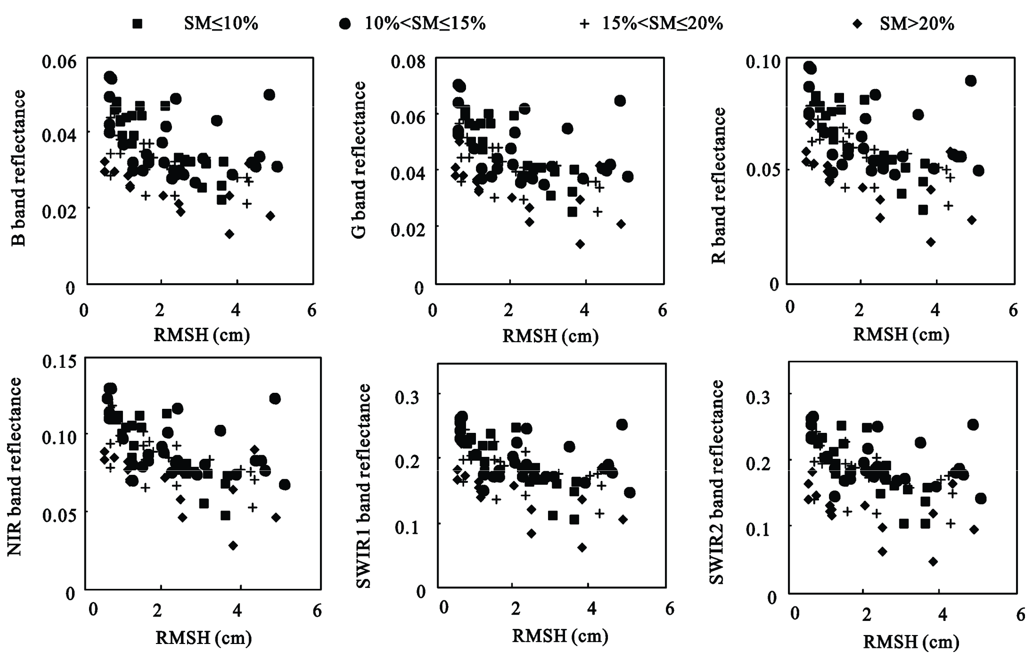

Fig. 4 Single-band SR variation with RMSH under constant SM conditions

new variable was added, a test was made to check if some variables can be deleted without significantly increasing the residual sum of squares. The way to test errors in models created by multiple nonlinear regression relied on *F*-statistic, *MSE* (mean square error), and R^2. The procedure was finalized when the R^2 significantly increased or when the *MSE* and *F*-statistic scale fell below a critical value. The results are shown in Table 4 and Table 5.

As the number of used bands increased, the adjusted R^2 increased and the *MSE* values significantly decreased ($F_{sig} < 0.01$), as indicated in Table 4 and Table 5. When more than four bands were used, the adjusted R^2 and *MSE* were generally constant. After repeated comparison and analysis, four different bands were used for predicting soil moisture and soil surface roughness. The verification results are shown in Fig. 5.

The test parameters of the simulation equation used in Fig. 5 clearly show that all the equations were satisfied and of high reliability. When the four bands were used, the R^2 reached the maximum and the *MSE* no longer decreased. After comparative analysis, the four

Table 4 Regression statistics models for estimating soil moisture based on multi-band spectral reflectance

Model	Reflectance of different bands	Model coefficients							Overall statistics		
		a	b_1	b_2	b_3	b_4	b_5	b_6	R^2	F_{sig}	*MSE*
M1-1	B, G	–0.38	–0.42	0.28	—	—	—	—	0.39	3.6301E–07	0.0019
M1-2	B, G, NIR	–0.04	0.90	–1.59	–0.72	—	—	—	0.68	2.2798E–14	0.0010
M1-3	B, G, SWIR2, NIR	0.00	0.62	–1.22	–0.11	0.72	—	—	0.70	1.8939E–14	0.0009
M1-4	B, G, SWIR2, NIR, SWIR1	–0.03	0.58	–1.11	–0.23	0.55	0.24	—	0.70	6.7612E–14	0.0009
M1-5	B, G, SWIR2, R, NIR, SWIR1	–0.07	0.72	–1.59	–0.26	0.47	0.39	0.29	0.70	2.4623E–13	0.0009

Table 5 Regression statistics models for estimating soil surface roughness based on multi-band spectral reflectance

Model	Reflectance of different bands	Model coefficients							Overall statistics		
		c	d_1	d_2	d_3	d_4	d_5	d_6	R^2	F_{sig}	*MSE*
M2-1	NIR, R	13.16	–66.69	63.66	—	—	—	—	0.48	5.0798E-09	0.2024
M2-2	G, SWIR1, NIR	7.90	72.47	44.55	148.57	—	—	—	0.72	7.9942E-16	0.1085
M2-3	NIR, R, G, SWIR1	6.80	–135.62	–61.06	130.02	45.44	—	—	0.72	4.7816E-15	0.1094
M2-4	NIR, R, G, SWIR1, B	5.79	–135.97	–30.28	14.59	46.05	95.38	—	0.71	2.6021E-14	0.1106
M2-5	NIR, R, G, SWIR1, B, SWIR2	5.70	–149.48	–9.19	11.85	53.07	84.60	4.89	0.71	1.2689E-13	0.1120

Notes: R^2 is the squared adjusted multiple correlation coefficient and F_{sig} is the probability of F statistic. All models were significantly different for $F_{sig} < 0.001$. *MSE* is the mean squared error

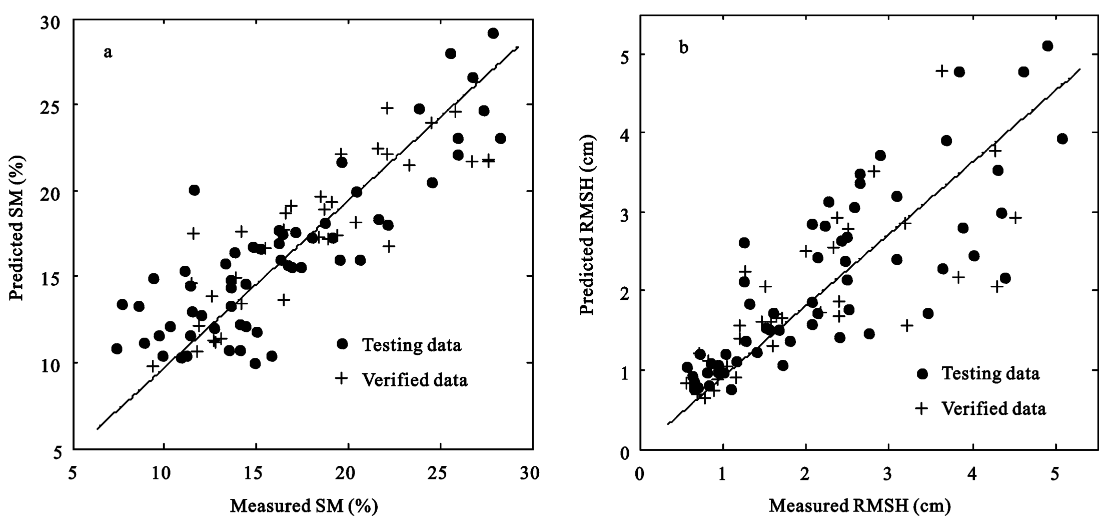

Fig. 5 Predicted and measured soil moisture and soil surface roughness

characterized bands, which are B (485 nm), G (555 nm), SWIR2 (2200 nm) and NIR (845 nm), were selected as the independent variables to estimate soil moisture. It was found that the predicted SM values were strongly correlated with in-situ SM (Fig. 5), and the R^2 and root mean square error (*RMSE*) values were 0.62 and 2.6%, respectively. Using NIR (845 nm), R (675 nm), G (555 nm), and SWIR1 (1600 nm) as independent variables to estimate the soil surface roughness resulted in weaker correlations; the R^2 and *RMSE* (root mean square error) values were 0.48 and 0.69 cm, respectively.

For soil moisture and soil surface roughness predictions within 7.4%–28.2% and 0.56–5.08 cm, respectively, using the characteristic bands of reflectivity, Equations (6) and (7) are proposed.

$$SM = 0.62\ln SR_{\mathrm{B}} - 1.22\ln SR_{\mathrm{G}} - 0.11\ln SR_{\mathrm{SWIR2}} + 0.72\ln SR_{\mathrm{NIR}} \tag{6}$$

$$RMSH = 6.8\times \mathrm{e}^{(-135.62SR_{\mathrm{NIR}} - 61.06SR_{\mathrm{R}} + 130.02SR_{\mathrm{G}} + 45.44SR_{\mathrm{SWIR1}})} \tag{7}$$

where the used characteristic bands of soil moisture are blue, green, SWIR2, and NIR, and the characteristic bands of soil surface roughness are NIR, red, green, and SWIRl. These two equations provide a new way to predict surface roughness and moisture of bare soils using spectral reflectance measured under field condition.

4 Discussion

4.1 Performance of SM and RMSH estimation model

The difference between an indoor and outdoor experiment is that the RMSH of the screened and ground soil samples measured in the laboratory is of uniform roughness, while the fluctuation range of RMSH under field conditions is relatively large. To demonstrate the influence of RMSH on SM estimation model and to analyze the applicability of the RMSH models, SM and RMSH were re-fitted at four levels. The fitting results obtained by multiple nonlinear regression analysis using these data, and based on Equation (6) and Equation (7), are shown in Table 6 and Table 7.

According to Table 6, the form of logarithmic equation clearly yielded results very similar to Equation (6), and there were no significant differences for R^2 and *MSE*, but the regression coefficients varied for different RMSH levels. To study the influence of RMSH on SM estimation models, soil SR of three larger RMSH levels were introduced into the estimation model of RMSH1; the introduced RMSH levels were RMSH2, RMSH3, and RMSH4. Additionally, the obtained R^2 and *RMSE* of the fitting equation between the estimated and the verified data were 0.83 and 2.7%, 0.81 and 3.0%, and 0.55 and 3.6% for the levels RMSH2, RMSH3, and RMSH4, respectively. R^2 decreased when the correlation of RMSH1 was individually adjusted on RMSH2, RMSH3, and RMSH4. Nevertheless, *RMSE* increased with intensely increasing the RMSH level. The performances of RMSH1 soil moisture estimation for high RMSH levels (i.e., RMSH4) were so poor that *RMSE* reached 3.6% and R^2 was as low as 0.55. This proved that the SM estimation model is sensitive to RMSH and the correlation between SR and SM obtained under a single roughness condition cannot be applied to other roughness levels. The SM estimation accuracy of this method in practical application is therefore limited. According to the actual situation of the farmland surface, various soil surface roughness conditions were designed in this study; the correlation between SM and SR based on these data is more applicable. In other words, within a certain range (0.56–4.31 cm), the soil moisture can be estimated based on Equation (6) without considering the effect of soil surface roughness.

Table 6 Regression statistics models for estimating soil moisture based on the same RMSH level

Model	Model coefficients					Overall statistics		
	a	b_1	b_2	b_3	b_4	R^2	F_{sig}	MSE
Equation (6)	0.00	0.62	–1.22	–0.11	0.72	0.70	1.89E–14	0.0009
RMSH1 level	0.01	0.72	–1.39	–0.09	0.79	0.83	3.38E–07	0.0006
RMSH2 level	0.06	0.20	–0.89	–0.24	0.98	0.86	5.51E–08	0.0006
RMSH3 level	0.01	0.20	–0.72	–0.20	0.71	0.84	2.95E–07	0.0006
RMSH4 level	–0.13	0.18	–0.65	–0.10	0.54	0.57	2.30E–03	0.0014

Table 7 Regression statistics models for estimating soil surface roughness based on the same SM level

Model	Model coefficients					Overall statistics		
	c	d_1	d_2	d_3	d_4	R^2	F_{sig}	MSE
Equation (7)	6.80	–135.62	–61.06	130.02	45.44	0.72	4.78E–15	0.1094
SM1 level	4.65	–45.98	–185.04	174.07	35.46	0.90	3.96E–08	0.0391
SM2 level	9.44	–239.34	276.42	–134.47	45.30	0.52	9.84E–04	0.2409
SM3 level	8.71	–160.97	–172.48	294.66	54.84	0.81	1.51E–05	0.0976
SM4 level	3.09	–62.59	–322.47	376.84	42.13	0.56	6.00E–02	0.3467

The RMSH under different SM conditions were estimated by using multiple nonlinear regression. The form of the exponential equation fitting is similar to Equation (7) and the difference between R^2 and MSE was not significant (Table 7). To study the influence of SM on RMSH estimation model, soil spectral reflectance with three larger soil moisture levels were introduced into the estimation model of SM1; the introduced SM levels were SM2, SM3, and SM4. Moreover, the obtained R^2 and $RMSE$ of the fitting equation of the estimated data and the verified data were 0.20 and 1.29 cm, 0.81 and 1.07 cm, and 0.53 and 0.91 cm for the levels SM2, SM3, and SM4, respectively. RMSE increased with the increasing SM level. This indicates that the RMSH estimation model is sensitive to SM and the regression equation between SR and RMSH obtained under consistent moisture condition cannot be applied to other moisture levels. Therefore, the soil surface roughness can be estimated based on Equation (7) within a certain soil moisture range (7.4%–28.2%).

4.2 Estimation uncertainty of SM and RMSH based on single soil type

In this study, it was concluded that SR correlates to soil parameters for a single soil type, which is consistent with other studies (Croft et al., 2012b). But the influences of different soil types with varying biochemical properties on multiple nonlinear regression have not yet to be considered in this study. As the experimental plots had the same soil type, there was no obvious variation in SR curves as a result of different absorption features. However, differences might exist among fields for the estimation of soil parameters in large areas. Croft et al. (2012b) pointed out that there are clear differences in reflectance spectra for different soil types; the differences were observed in baseline reflectance and more surface-specific, the wavelength dependent absorption features. The reflectance of a soil does not only change as a function of soil moisture and soil surface roughness, but is affected by main soil properties, such as soil organic matter (SOM) contents and texture (Irons et al., 1989).

Generally, there are many ways to classify soils, one is texture. The impact of soil texture on soil SR is mainly reflected by two aspects. On the one hand, texture affects the water holding capacity; indeed, relatively large particles can hold more air and water, which affects the soil SR. On the other hand, the size of soil particles has a significant influence on the soil SR; relatively small particles are tightly bound which creates a smooth soil surface of relatively high reflectivity. The chemical composition of soil particles with different grain sizes also affects soil spectral reflectance. Wight et al. (2016) suggested that texture is the principal characteristic that interferes with the model's accuracy, and it affects the spectral reflectance in the entire Vis-NIR region. As a result, soil texture must be considered as a driving factor for modeling soil moisture, which leads to improved modeling according to each soil category.

Mouazen et al. (2006) found that the interaction between other soil properties may perturb the signal under field conditions based on RMSH. Soil spectra are complex, and soil properties interact in complex ways, masking the correlations between specific spectral reflectance signatures and a specific soil property. Lobell and Asner (2002) concluded that soil surface moisture and soil organic carbon (SOC) contents have a similar impact on reflectance as soil surface roughness, whereby baseline reflectance is reduced with relatively higher soil moisture and SOC contents. These spectral variations present a challenge for the estimation of soil moisture and soil surface roughness when different soil types are considered. The directional index approach has been used for acquiring soil surface roughness (Croft et al., 2009; 2012a), and the impact of soil biochemical variations was neglected and more accurate soil surface roughness was retrieved across different soil types.

In this study, the models were developed under field conditions and the soil type was the same for all the sub-regions (chernozem); But the variations caused by soil types must be considered in future studies.

5 Conclusions

This study focused on the prediction of SM and RMSH of farmland bare soils using SR. An experimental area of three soil moisture levels and four soil surface roughness levels was set up to analyze the correlation between SR and RMSH, and SR and SM. Compared with previous laboratory studies, this paper also focused on the clods and aggregates randomly distributed on the farmland surface. Agricultural treatments and rainfall were fully considered by experimental area selection and data observations during each experiment. Significant negative correlations were observed from the collected spectral reflectance curves between SR and RMSH, and between SR and SM. It was concluded from the spectral reflectance curves that an 80% increase in reflectance was associated with a decrease in soil surface roughness (from 4.31 to 0.56 cm) and a 40% decrease in reflectance was associated with an increase in soil moisture (from 11.4% to 27.7%).

According to the correlations between single-band reflectance and the soil parameters, soil moisture and soil surface roughness were each determined as two independent variables. The characteristic bands that were used to predict soil surface roughness were determined by stepwise multiple nonlinear regression methods. Four characterized bands were selected to estimate the SM, which are B (485 nm), G (555 nm), SWIR2 (2200 nm), and NIR (845 nm). The predicted soil moisture values were strongly correlated with measured values, and the adjusted R^2 and *RMSE* values were equal to 0.62 and 2.6%, respectively. Using NIR (845 nm), R (675 nm), G (555 nm), and SWIR1 (1600 nm) as variables to estimate the RMSH resulted in correlations of adjusted R^2 and *RMSE* values equal to 0.48 and 0.69 cm, respectively. It was found that soil moisture and soil surface roughness can be accurately estimated by multi-band spectral reflectance under field condition.

The characteristic bands used for the predicting model coincide with the center wavelength of the commonly used optical satellite sensors. Finally, understanding these correlations and developing their basis correction methods can be applied for the prediction of soil parameters based on the satellite and UAV optical image for precision agriculture in the future.

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