

Article

Influences of Soil Bulk Density and Texture on Estimation of Surface Soil Moisture Using Spectral Feature Parameters and an Artificial Neural Network Algorithm

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Abstract: Effective monitoring of soil moisture (θ) by non-destructive means is important for crop irrigation management. Soil bulk density (ρ) is a major factor that affects potential application of θ estimation models using remotely-sensed data. However, few researchers have focused on and quantified the effect of ρ on spectral reflectance of soil moisture with different soil textures. Therefore, we quantified influences of soil bulk density and texture on θ , and evaluated the performance from combining spectral feature parameters with the artificial neural network (ANN) algorithm to estimate θ . The conclusions are as follows: (1) for sandy soil, the spectral feature parameters most strongly correlated with θ were S_g (sum of reflectance in green edge) and $A_{Depth780-970}$ (absorption depth at 780–970 nm). (2) The θ had a significant correlation to the $R_{900-970}$ (maximum reflectance at 900–970 nm) and $S_{900-970}$ (sum of reflectance at 900–970 nm) for loamy soil. (3) The best spectral feature parameters to estimate θ were $R_{900-970}$ and $S_{900-970}$ for clay loam soil, respectively. (4) The $R_{900-970}$ and $S_{900-970}$ showed higher accuracy in estimating θ for sandy loam soil. The $R_{900-970}$ and $S_{900-970}$ achieved the best estimation accuracy for all four soil textures. Combining spectral feature parameters with ANN produced higher accuracy in estimating θ ($R^2 = 0.95$ and $RMSE = 0.03 \text{ m}^3 \text{ m}^{-3}$) for the four soil textures.

Keywords: bulk density; spectral characteristics; artificial neural networks; soil water content



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1. Introduction

Soil erosion, salinity, and compaction are influenced by soil moisture (θ) [1]. Soil moisture at the soil surface layer is not only a major influential factor of crop growth and yield in agriculture [2], but is also a crucial indicator of soil dryness in arid and temperate regions [3,4]. Accurate measures of θ contribute to drought analysis [5], irrigation management, and flood prediction [6,7]. In addition, θ is an important parameter frequently used in crop and hydrology models [8,9]. Therefore, fast and effective estimation of θ is important for agriculture, ecology, meteorology, etc. [10].

Traditional methods of obtaining θ are the gravimetric [11], heat pulse probe [12], soil moisture sensor [13], and neutron probe [14] methods. Nevertheless, these methods also have disadvantages. The gravimetric method lacks the ability to rapidly monitor θ during plant growth stages [11]. The heat pulse method is time-consuming and labor-intensive. The shortcomings of the soil moisture sensor and neutron probe methods are their high costs and risk of radiation exposure. By contrast, remote sensing technology can provide an effective and fast method for estimating θ . The first study showed that it is feasible to

estimate θ by soil spectral reflectance, and reported that soil spectral reflectance decreases exponentially with soil moisture [15].

Since that first study, numerous studies have concluded that soil spectral reflectance and θ have a non-linear relationship [1,4,5,16–22]. Other researchers have demonstrated a high correlation between θ and near-infrared spectral reflectance [18,19,21,23,24], and this relationship is affected by soil texture [12,17,25]. Soil moisture has been estimated by ground penetrating radar [26]. Compared with the visible spectral region (VIS), the study of [20] showed that the short-wave infrared region (SWIR) was more sensitive to θ . Other researchers have found that Landsat TM5 data provide the best θ estimation at the 5- and 15-cm soil layer when factored into an exponential model [11]. Many studies have reported the use of spectral indices to improve estimation accuracy of θ [11,22,24,27], such as the temperature vegetation dryness index that indicates relative soil moisture [28], and microwave polarization difference index that describes the spatial and temporal variations of soil moisture [29]. Although some researchers also studied the relationship between θ and spectral data obtained in situ; these field soil samples exhibited more variations than lab-produced samples exhibited in physical traits, such as soil compaction [30], surface roughness, and porosity.

Comparing past studies on the remote sensing estimation of θ has shown that simple statistical methods could not improve the accuracy of estimating soil moisture content [4,5,11,16,18–20,22]. Artificial neural network (ANN) is a nonlinear machine learning technique that is non-parametric, meaning the number of input parameters can be controlled without considering input statistical characteristics during simulation [7]. Some researchers employed ANNs to obtain high estimation accuracy of θ using remotely-sensed data [7,14,31–33], because more effective spectral feature information were considered.

To date, most studies on estimating θ have been focused on lab using spectroscopic technology [15,18–21]. Additionally, few researchers have focused on and quantified the effects of soil bulk density (ρ) on soil moisture spectral reflectance in soil samples of different soil textures. Because bulk density and soil texture are major influential factors when applying remote sensing technology in the field, we investigated their effects on estimating θ using a strategy of combining spectral feature parameters data with an ANN. The relationships between θ , soil bulk density, soil texture (sandy, loam, clay loam, and sandy loam) and soil reflectance were investigated. Soil reflectance was obtained using a portable spectroradiometer. The advantage of an ANN is that they can fit nonlinear relations. The motivations of this study are three-fold: (i) to analyze and quantify the effects of soil bulk density (ρ), texture, and θ on spectral reflectance; (ii) to estimate moisture content in soils of various ρ and soil textures using spectral feature parameters and an ANN algorithm; and (iii) to compare the performance of various models. This study indicates that combining an ANN with spectral feature parameters will improve accuracy in estimating θ .

2. Material and Methods

2.1. Soil Sample Preparation

Four textures of soil (sandy (S1), loam (S2), clay loam (S3), and sandy loam (S4); Table 1) with different soil bulk densities were selected to analyze and quantify the relationships between soil moisture (θ) and spectral feature parameters. Each soil sample was air-dried before sieving through a 2-mm mesh screen to better homogenize the particles and remove debris and roots. Sieved soils were then oven-dried at 105 °C for one day. Particle density was determined by the pycnometer method from Heiskanen [34], soil organic matter (SOM) was determined by the potassium dichromate method [4], and particle-size distribution (PSD) was measured by the pipette method [35]. The soil porosity was calculated according to different soil densities. It is assumed that the soil porosity was filled with soil moisture; that is, the soil porosity was the saturated water content of this soil density. The range of soil water content was from the dried soil to the saturated water soil, evenly divided into ten parts. The soil quality and the corresponding soil water

content of a particular soil density was calculated according to the volume of aluminum box. Water and soil were mixed, and then each soil sample was homogenized and sealed in a plastic bag to allow the moisture to equilibrate across the sample for 48 h at 25 °C. No more than 2 h after the end of the equilibration period, these soil samples were packed into separate aluminum containers (diameter = 5.5 cm and height = 1 cm) and covered (Figure 1). Values of θ and ρ are listed in Table 2. Three replicates were prepared at each treatment. A total of 453 samples were obtained. Each soil sample was carried out via spectrometric measurement.

Table 1. Characteristics of the four soil textures.

Soil Texture	Sand (0.02–2 mm, %)	Silt (0.002–0.02 mm, %)	Clay (<0.002 mm, %)	Particle Density (g cm ⁻³)	SOM (g kg ⁻¹)
Sandy soil	88.80	0	11.20	2.68 ± 0.02	1.30
Loamy soil	43.60	40.00	16.40	2.58 ± 0.02	10.90
Clay loam soil	28.00	34.67	37.33	2.68 ± 0.09	8.20
Sandy loam soil	73.60	13.33	13.07	2.50 ± 0.09	17.20

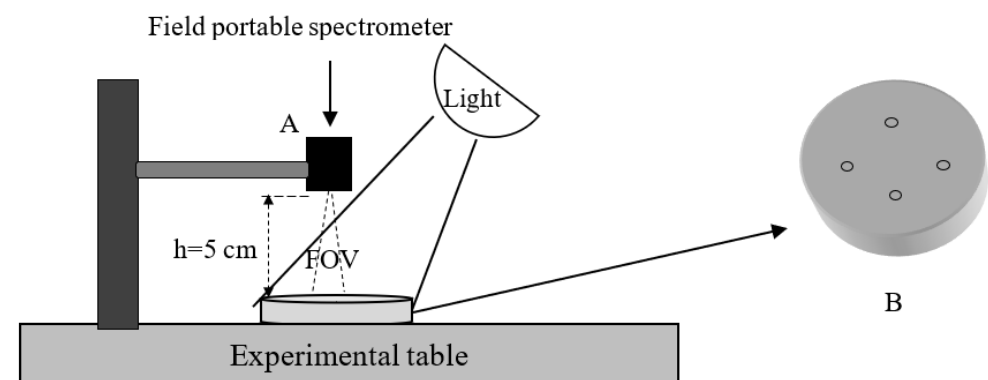


Figure 1. Schematic diagram of spectrum measurement in field portable spectrometer (A) and measuring spectral location in soil surface (B).

Table 2. Soil moisture (θ) treatments in each of the four soil texture groups.

Soil Texture	Soil Bulk Density (g cm ⁻³)	Soil Moisture (m ³ m ⁻³)	Treatments
Sandy soil	1.40	0–0.33	8
	1.50	0–0.42	11
	1.60	0–0.40	11
	1.70	0–0.37	11
Loamy soil	1.20	0–0.42	9
	1.30	0–0.45	10
	1.40	0–0.46	11
	1.50	0–0.42	11
Clay loam soil	1.30	0–0.25	6
	1.40	0–0.34	8
	1.50	0–0.34	9
	1.60	0–0.39	11
Sandy loam soil	1.30	0–0.33	8
	1.40	0–0.29	8
	1.50	0–0.32	9
	1.60	0–0.32	10

2.2. Field Portable Spectrometer

A field portable spectrometer (GER 1500, Spectra Vista Corporation) was used to obtain the soil spectral reflectance data, which covered the UV, VIS, and NIR (near-infrared)

regions from 350 to 1050 nm; the field of view was 4°. The spectrometer was mounted on an iron stand at 5 cm above the aluminum container of soil (Figure 1A). A 75-W halogen lamp was located 30 cm from the soil sample and at an angle of 60° from the zenith (Figure 1A) to simulate rays of light shining over the sample area. The halogen lamp was connected to a regulation device to avoid possible variation in electrical power supply system. This experimental setup was chosen to minimize shadows. A white reference panel was used to calibrate the spectrometer before measuring each soil sample's reflectance. Considering the influence of potential variation in surface roughness across the surface area of soil packed in each aluminum container and kept the soil surface smooth. Reflectance was measured from four points in the aluminum container with each point selected after rotating 90 degrees (Figure 1B). The aperture measurement of this spectrometer depends on the measurement height. In this study, the measurement height was 5 cm. The aperture measurement, the measurement area and the soil surface area were 0.35 cm, 0.1 cm², and 23.75 cm², respectively. The four points of spectral data were averaged to obtain a mean reflectance value for each soil sample. The percentage of the 4 points on total soil surface area was 1.63%. Measurements of θ were obtained by the gravimetric method.

2.3. Selection of Spectral Feature Parameters

In order to enhance the differences in absorption and reflectance, continuum removal was applied to the full spectrum data [36]. The presence of soil moisture can change the shape of the spectral reflectance curve and values measured of spectral features [1,17,19,37]. A nonlinear correlation exists between soil spectral reflectance and soil moisture [16,22,23,38,39]. To simplify data analysis and reduce the spectral dimension, the sensitive spectral reflectance data to soil moisture were selected to keep as much spectral information as possible. Different spectral feature parameters were used to describe the location of each absorption and reflection band. The spectral feature parameters included absorption depth, absorption area, normalized absorption depth [1,40–42], maximum reflectivity, and sum reflectivity (Table 3). Previous studies have shown that the absorption of spectra at 760 and 970 nm are useful for the estimation of soil moisture [43–46].

Table 3. The selected spectral feature parameters.

Title	Definition and Description	Formula
R _b	Maximum reflectance with blue edge (490–530 nm)	max(R _b)
S _b	Sum reflectance with blue edge	$\sum R_b$
R _y	Maximum reflectance with yellow edge (550–580 nm)	max(R _y)
S _y	Sum reflectance with yellow edge	$\sum R_y$
R _g	Maximum reflectance with green peak	max(R _g)
S _g	Sum reflectance with green edge (510–560 nm)	$\sum R_g$
R _r	Maximum reflectance with red peak	max(R _r)
S _r	Sum reflectance with red edge (580–680 nm)	$\sum R_r$
R _o	Lowest reflectance with red edge	min(R _y)
R _{900–970}	Maximum reflectance with 900–970 nm	max(R _i)
S _{900–970}	Sum reflectance with 900–970 nm	$\sum R_i$
A_Depth _{500–670}	Absorption depth feature in 500–670 nm	1-min(R _i)
A_Area _{500–670}	Absorption area feature in 500–670 nm	$\int_{R_{si}}^{R_{ei}} (R_{ci} - R_i) di$
A_ND _{500–670}	Normalized absorption depth in 500–670 nm	A_Depth _i / A_Area _i
A_Depth _{780–970}	Absorption depth feature with 780–970 nm	1-min(R _i)
A_Area _{780–970}	Absorption area feature in 780–970 nm	$\int_{R_{si}}^{R_{ei}} (R_{ci} - R_i) di$
A_ND _{780–970}	Normalized absorption depth in 780–970 nm	A_Depth _i / A_Area _i
A_Depth _{560–760}	Absorption depth feature in 560–760 nm	1-min(R _i)
A_Area _{560–760}	Absorption area feature in 560–760 nm	$\int_{R_{si}}^{R_{ei}} (R_{ci} - R_i) di$
A_ND _{560–760}	Normalized absorption depth in 560–760 nm	A_Depth _i / A_Area _i

Note: R_{ci} and R_i are the reflectance of the continuum line and reflectance at the corresponding wavelength i. in the absorption area; and R_{si} and R_{ei} are the start and the end wavelengths in each absorption area.

2.4. Artificial Neural Network Algorithm

The ANN consisted of three neural layers, an input layer, a hidden layer, and an output layer. A feed-forward back propagation algorithm was used to train the neural network before it could be used to estimate θ from the selected spectral features (Figure 2). Firstly, 20 spectral feature parameters comprised the input layer. Secondly, the spectral feature parameters were trained by the “trainlm (It is named Levenberg-Marquardt BP algorithm function, which is a network training function that updates weight and bias values according to Levenberg-Marquardt optimization [47])” function to construct the estimation model, and the training function of the neural network was in the hidden layer, learning to adapt to the environment using the function “learngdm”. Finally, the function “tansig” as well as the transfer function of the hidden layer were used in the output layer. MATLAB 2019b software (MathWorks, Natick, MA, USA) was used to run the ANN. The output of the ANN model was calculated by the following equation:

$$y = f^2 (w^2 f^1 (w^1 x + b^1) + b^2) \quad (1)$$

where y is the output vector (estimated θ); x is the input vector (spectral feature parameters); f^1 and f^2 are transfer functions of the hidden and output layers, respectively; b^1 and b^2 are biases of the hidden and output layers, respectively; and w^1 and w^2 are weights of the input and hidden layers, respectively.

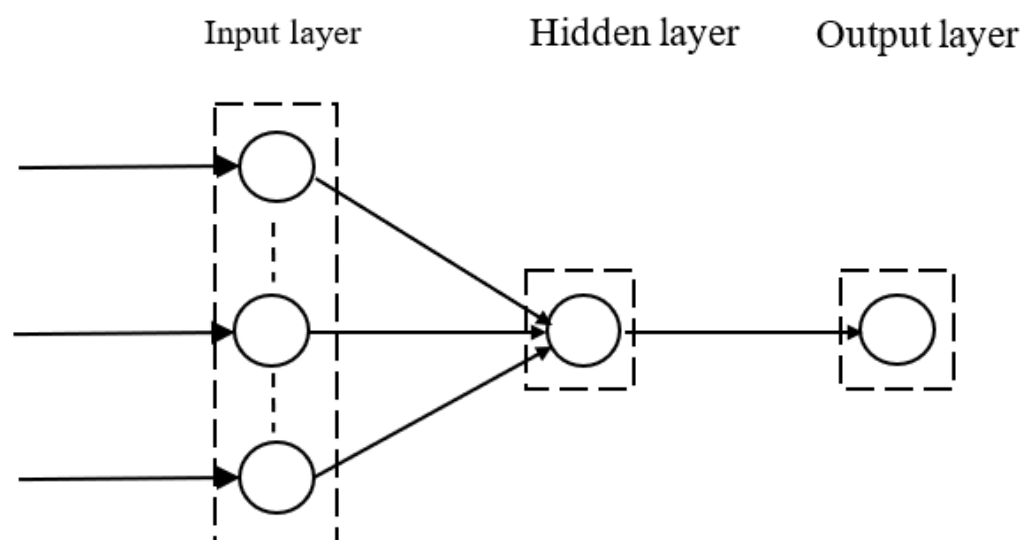


Figure 2. The schematic chart of artificial neural network.

2.5. Data Analysis

The relationships between the measured and estimated values were corroborated using estimation error statistics, such as the coefficient of determination (R^2) and root mean square error (RMSE). All data were divided into two groups to build and validate regression model and analyzed by the Statistical Package for the Social Sciences software (SPSS 17.0, Chicago, IL, USA). Linear or multiple regression analysis was performed to determine the relationships between spectral feature parameters and θ . The higher the R^2 and the lower the RMSE values of a model indicated better estimation precision and accuracy of θ .

3. Results

3.1. Soil Reflectance Trend with Different Soil Moisture Levels and Bulk Densities

The results showed that soil reflectance was increased with the decrease of soil moisture under certain conditions of soil bulk density and soil texture (Figure 3). There was also a positive relationship between soil reflectance and soil bulk density for the same soil

textures. Our findings were consistent with previous studies, there is a positive correlation between soil reflectance and bulk density [1,4,30,48–50]. Soil particle size distribution, soil moisture, and distribution of soil porosity, which affect the path of light transmission [30,51,52], may explain the relationships observed.

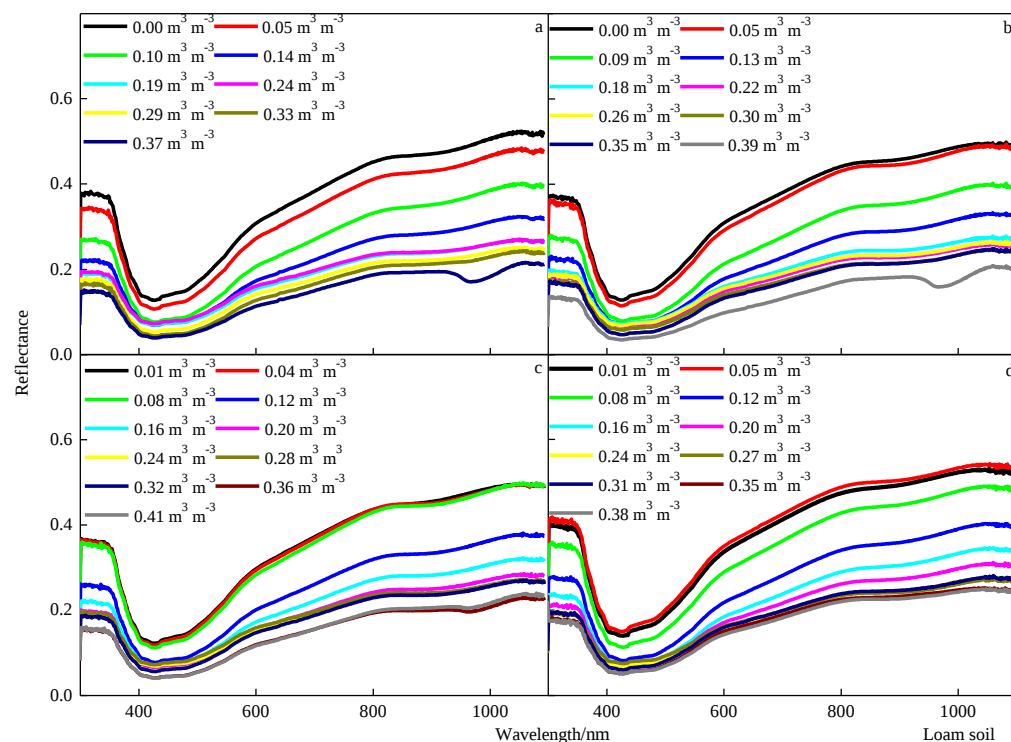


Figure 3. Soil reflectance with different soil moisture and bulk density in loamy soil. Soil bulk density (ρ) was 1.20 g cm^{-3} (a), $\rho = 1.30 \text{ g cm}^{-3}$ (b), $\rho = 1.40 \text{ g cm}^{-3}$ (c), and $\rho = 1.50 \text{ g cm}^{-3}$ (d).

Our results also presented that soil reflectance was sharply decreased in sandy soil compared with other soils (loamy, clay loam, and sandy loam soils) at the soil moisture level of $0.10 \text{ m}^3 \text{ m}^{-3}$, and the reflectance in loamy soil was higher than that of the other three soils under the same soil bulk densities (Figure 4). The phenomenon found in the sandy soil was likely due to the properties of this soil texture; sand grains easily form more macropores because of the larger particle size of sand compared to the smaller sizes in the other soil types [17,30,52–54]. This phenomenon has also been reported in previous studies [1,18,30,46] and is probably a result of the soil organic matter and soil particles [18,41,46,55]. The very fine particles in clay soil are liable to form micropores, which may have resulted in greater porosity. Moreover, reflectance is increased with the higher clay content of the same soil bulk density because soil porosity is declined [17,46]. The authors of [19] reported a minor decrease of θ over 20% in reflectance of the VIS region, while reflectance of the SWIR region was not saturated until at a much higher soil moisture level, which was what we also observed in this study (Figures 3 and 4).

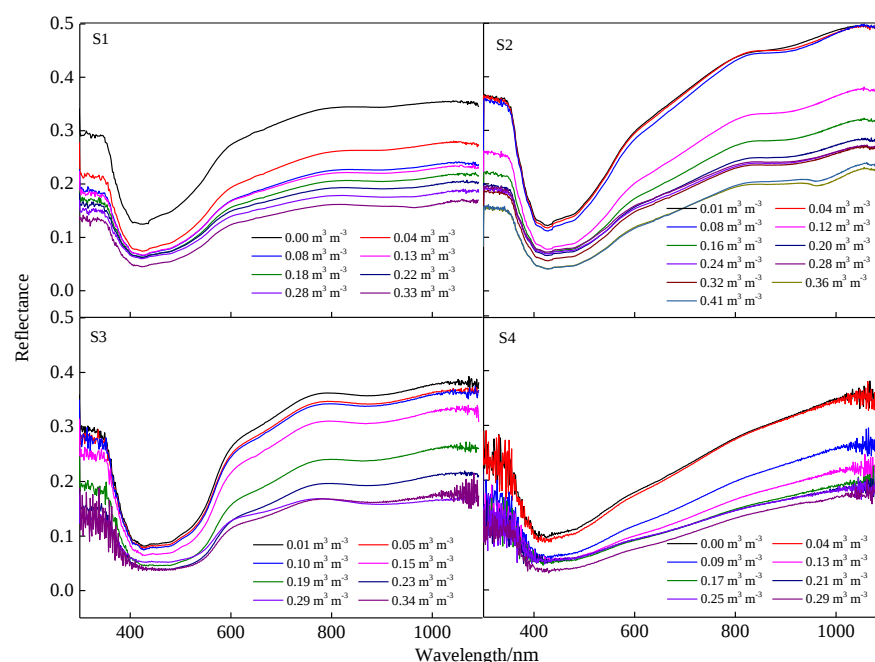


Figure 4. Soil reflectance with different soil texture under $\rho = 1.40 \text{ g cm}^{-3}$; sandy soil (S1), loamy soil (S2), clay loam soil (S3), and sandy loam soil (S4).

3.2. Relationships between Soil Moisture and Spectral Feature Parameters with Different Soil Bulk Densities

Significant negative correlations with spectral feature parameters were observed in the soil moisture (θ) estimation. They were exponential regressions for four soil texture. There were highly correlated relationships between θ and spectral feature parameters (especially $R_{900-970}$, $S_{900-970}$, and R_b) in sandy soil with bulk densities (ρ) of 1.40, 1.50, and 1.70 g cm^{-3} , with the exception of $A_{\text{Depth}500-670}$, $A_{\text{ND}780-970}$, and $A_{\text{Depth}560-760}$. When ρ was 1.60 g cm^{-3} , $R_{900-970}$, $S_{900-970}$ and $A_{\text{ND}560-760}$ could accurately estimate θ (R^2 was more than 0.92). In contrast, $A_{\text{Depth}500-670}$, $A_{\text{ND}500-670}$, $A_{\text{Depth}560-760}$, and $A_{\text{Depth}780-970}$ were no correlation with θ (Figure 5 and Appendix A Tables A1 and A2). For loamy soil, the $R_{900-970}$ and $S_{900-970}$ had the best correlated with θ for different ρ . There were no significant correlated relationships between $A_{\text{Depth}500-670}$, $A_{\text{Depth}780-970}$, and $A_{\text{Depth}560-760}$ and θ when soil bulk densities were set at 1.20, 1.30, and 1.50 g cm^{-3} . The $A_{\text{Depth}780-970}$ and $A_{\text{Depth}560-760}$ could not estimate θ , while soil bulk density was set at 1.40 g cm^{-3} (Figure 6 and Appendix A Tables A3 and A4).

The spectral feature parameters of clay loam soil with soil bulk density (ρ) of 1.30 g cm^{-3} showed that R_r , $R_{900-970}$, and $S_{900-970}$ had highly significant correlated relationships of θ with the exceptions of $A_{\text{Depth}500-670}$, $A_{\text{Depth}780-970}$, $A_{\text{Depth}560-760}$, and $A_{\text{ND}560-760}$. The estimation model of θ based on R_r and $A_{\text{Area}780-970}$ had the highest R^2 values (0.90 and 0.91) and lowest RMSE ($0.04 \text{ m}^3 \text{ m}^{-3}$), when ρ was 1.40 g cm^{-3} . In contrast, the relationships between $A_{\text{Depth}500-670}$, $A_{\text{Depth}560-760}$ and θ were not significant. The $R_{900-970}$ and $A_{\text{ND}560-760}$ were best correlated with θ with the ρ of 1.50 g cm^{-3} . The θ was the least significantly associated with $A_{\text{ND}780-970}$ and $A_{\text{Depth}560-760}$. The θ with the ρ of 1.60 g cm^{-3} was best significantly correlated with the $R_{900-970}$ and $S_{900-970}$ with the exception of $A_{\text{Depth}500-670}$ and $A_{\text{Depth}560-760}$ (Figure 7 and Appendix A Tables A5 and A6). Lastly, for sandy loam soil texture, the $A_{\text{Depth}500-670}$, $A_{\text{Depth}780-970}$, and $A_{\text{Depth}560-760}$ did not significantly with θ among the different soil bulk densities. Soil moisture was most significantly correlated to the $A_{\text{Area}500-670}$ and $A_{\text{Area}560-760}$, $A_{\text{Area}780-970}$ and $A_{\text{ND}780-970}$, $R_{900-970}$ and $S_{900-970}$, $A_{\text{Area}560-760}$ and R_o with ρ of 1.30, 1.40, 1.50, and 1.60 g cm^{-3} , respectively (Figure 8 and Appendix A Tables A7 and A8).

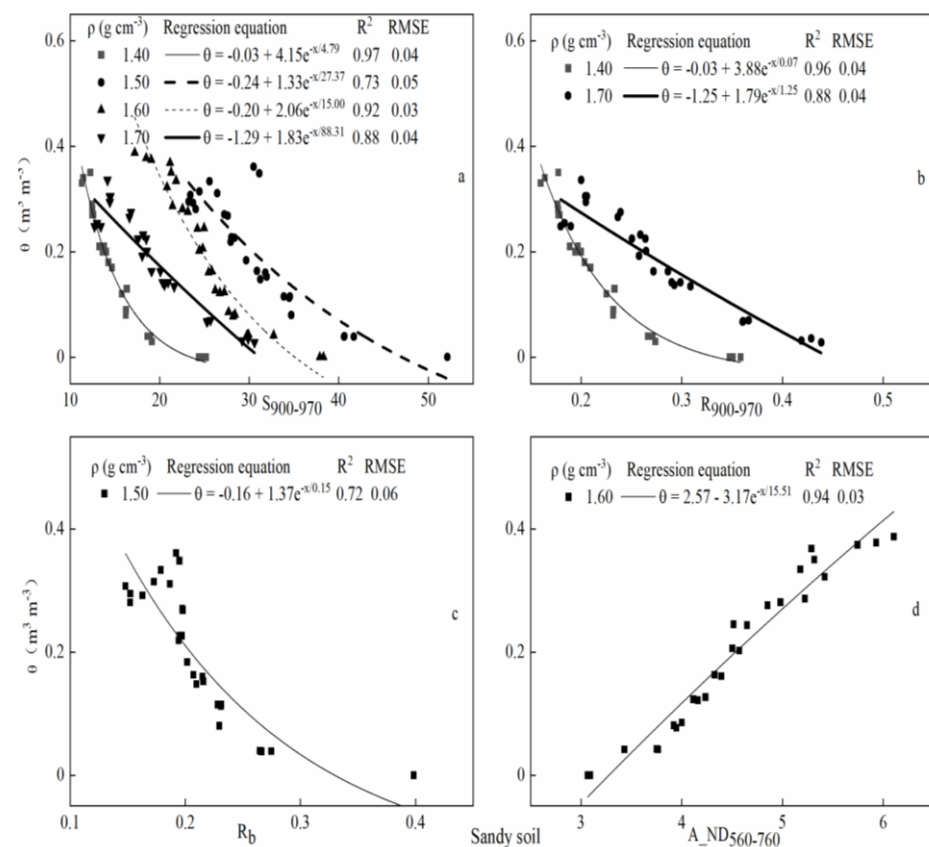


Figure 5. Relationships between soil moisture of sandy soil and spectral feature parameters ($S_{900-970}$ (a), $R_{900-970}$ (b), R_b (c) and $A_{ND560-760}$ (d)) under different soil bulk densities (ρ); ρ was 1.40 g cm^{-3} , $\rho = 1.50 \text{ g cm}^{-3}$, $\rho = 1.60 \text{ g cm}^{-3}$, and $\rho = 1.70 \text{ g cm}^{-3}$.

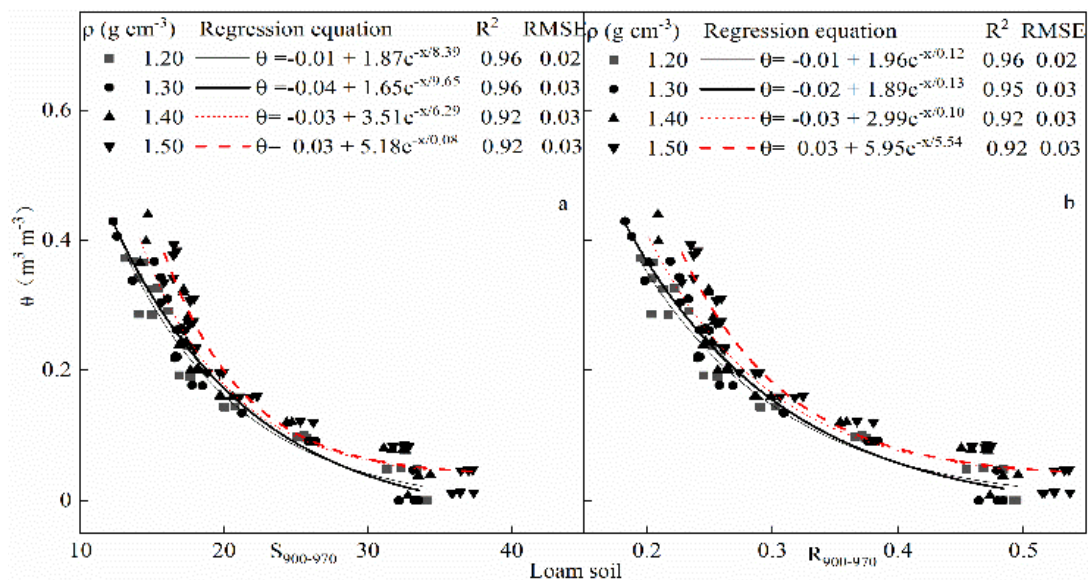


Figure 6. Relationships between soil moisture of loamy soil and spectral feature parameters ($S_{900-970}$ (a) and $R_{900-970}$ (b)) under different soil bulk densities (ρ). ρ was 1.20 g cm^{-3} , $\rho = 1.30 \text{ g cm}^{-3}$, $\rho = 1.40 \text{ g cm}^{-3}$, and $\rho = 1.50 \text{ g cm}^{-3}$.

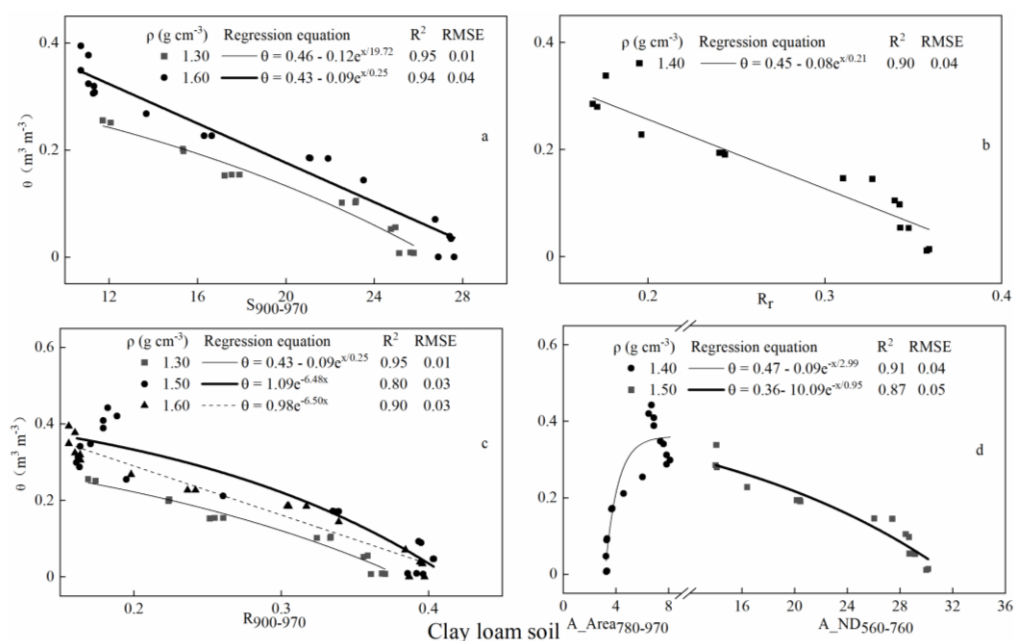


Figure 7. Relationships between soil moisture and spectral feature parameters ($S_{900-970}$ (a), R_r (b), $R_{900-970}$ (c), and $A_{\text{Area}_{780-970}}$ and $A_{\text{ND}_{560-760}}$ (d)) of clay loam soil under different soil bulk densities (ρ). ρ was 1.30 g cm^{-3} , $\rho = 1.40 \text{ g cm}^{-3}$, $\rho = 1.50 \text{ g cm}^{-3}$, and $\rho = 1.60 \text{ g cm}^{-3}$.

3.3. Soil Moisture Relationships with Spectral Feature Parameters Varied among Soil Textures

In the field, soil bulk density was influenced by external conditions, such as rainfall, farming practices and other human activities. Thus, the θ estimation model was considered the effect of soil bulk density in this study. The relationships found between θ and spectral feature parameters based on exponential regressions for the different soil textures with different bulk densities are shown in Tables 4 and 5. Among the results obtained, the θ estimation model had the highest R^2 values based on $A_{\text{Depth}_{780-970}}$ for the sandy soil ($R^2 = 0.31$); on $R_{900-970}$ and $S_{900-970}$ for the loamy soil ($R^2 = 0.92$) and sandy loam soil ($R^2 = 0.85$); and on $R_{900-970}$, $S_{900-970}$ and $A_{\text{ND}_{560-760}}$ for the clay loam soil ($R^2 = 0.85$).

The θ estimation model is partially affected by soil particles. Our results are in agreement with the study of [1] that the estimated θ values are influenced by clay particles and that θ estimation was best when clay content is between 13.07% and 16.40%. In this study, the models determined for loamy soil, clay loam soil, and sandy loam soil were more accurate than the model determined for sandy soil, and this finding is supported by that of previous studies [1,50].

In order to improve the adaptability and flexibility of the estimation model, the data from the four types of soil were used to build another θ estimation model. The result showed there were significant correlations between the spectral feature parameters and θ , with the exceptions of $A_{\text{Depth}_{500-670}}$ and $A_{\text{Depth}_{560-760}}$. The spectral feature parameters $R_{900-970}$ and $S_{900-970}$ had the strongest correlations (R^2 was more than 0.47 and RMSE was less than $0.06 \text{ m}^3 \text{m}^{-3}$, Table 6). The estimation accuracy of this model based on the four types of soil was lower than the estimation accuracy of the models based on certain soil type. Hence, how to improve the estimation model accuracy was worth considering.

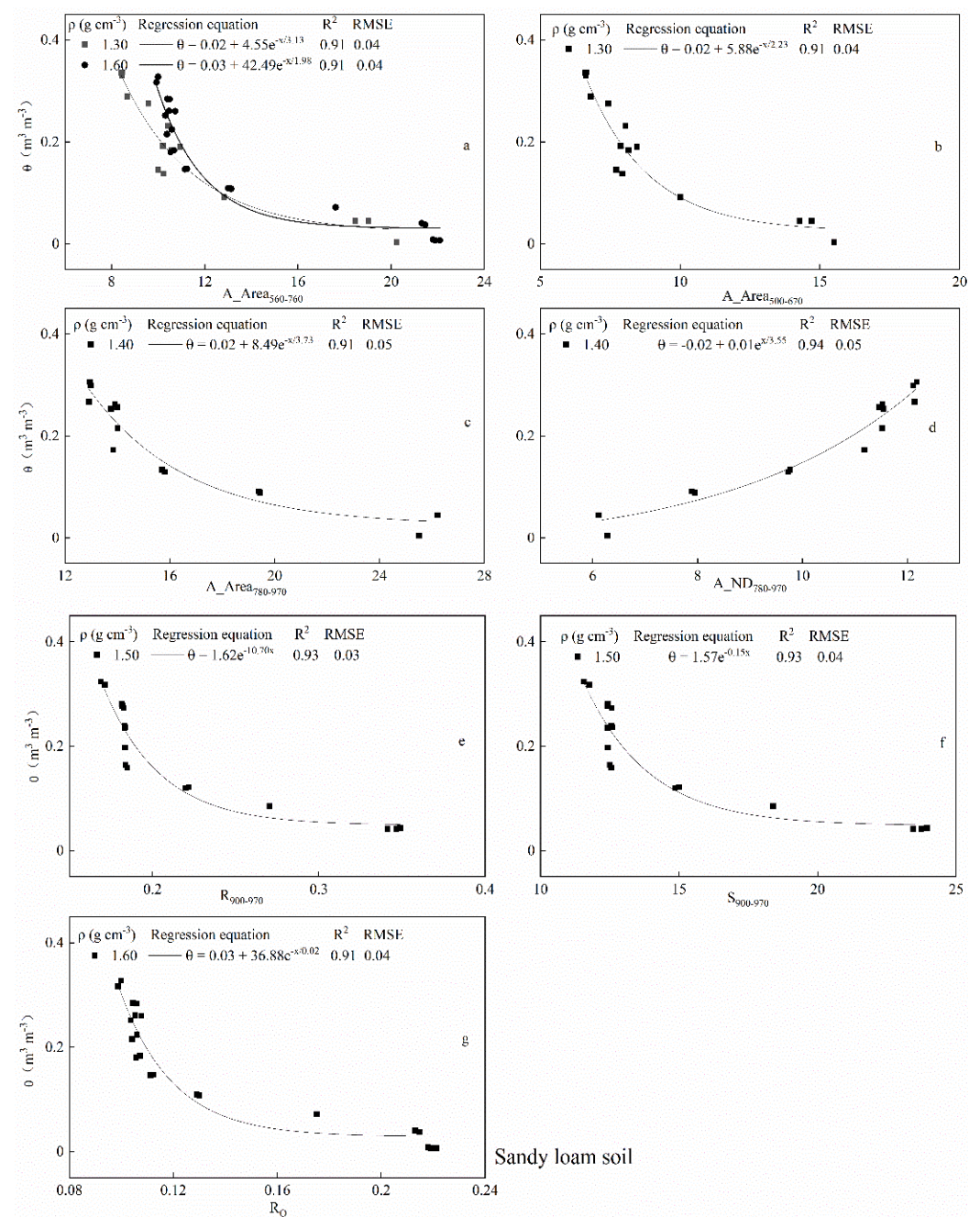


Figure 8. Relationships between soil moisture of sandy loam soil and spectral feature parameters ($A_Area_{560-760}$ (a), $A_Area_{500-670}$ (b), $A_Area_{780-970}$ (c), $A_ND_{780-970}$ (d), $R_{900-970}$ (e), $S_{900-970}$ (f), and R_o (g)) under different soil bulk densities (ρ). ρ was 1.30 g cm^{-3} , $\rho = 1.40 \text{ g cm}^{-3}$, $\rho = 1.50 \text{ g cm}^{-3}$, and $\rho = 1.60 \text{ g cm}^{-3}$.

Table 4. The θ regression models derived from spectral feature parameters for sandy and loam soils.

Spectral Feature Parameters	Sandy Soil ($n = 108$)	RMSE		Loamy Soil ($n = 105$)	RMSE	
	Regression Equation	R ²	m ³ m ⁻³	Regression Equation	R ²	m ³ m ⁻³
R _b	$\theta = 0.44 \times e^{-5.45x}$	0.23 *	0.09	$\theta = -0.01 + 1.41 \times e^{-x/0.06}$	0.87 **	0.04
S _b	$\theta = 0.44 \times e^{-0.15x}$	0.23 *	0.09	$\theta = -0.02 + 1.28 \times e^{-x/2.28}$	0.87 **	0.05
R _y	$\theta = 1.06 - 0.73 \times e^{x/1.31}$	0.22 *	0.09	$\theta = -0.01 + 1.68 \times e^{-x/0.08}$	0.87 **	0.04
S _y	$\theta = 1.28 - 0.95 \times e^{x/49.44}$	0.22 *	0.09	$\theta = -0.01 + 1.63 \times e^{-x/2.41}$	0.87 **	0.04
R _g	$\theta = 1.34 \times e^{-x/1.53}$	0.22 *	0.09	$\theta = -0.01 + 1.61 \times e^{-x/0.07}$	0.87 **	0.05
S _g	$\theta = 4.75 - 4.40 \times e^{x/247.62}$	0.24 *	0.09	$\theta = -0.01 + 1.45 \times e^{-x/3.18}$	0.87 **	0.04
R _r	$\theta = 0.60 - 0.29 \times e^{x/0.93}$	0.20 *	0.09	$\theta = 0.01 + 2.65 \times e^{-x/0.10}$	0.88 **	0.05
S _r	$\theta = 0.42 \times e^{-0.03x}$	0.19 *	0.09	$\theta = 2.32 \times e^{9.44x}$	0.87 **	0.05
R _o	$\theta = 0.43 \times e^{-3.23x}$	0.20 *	0.09	$\theta = -0.01 + 1.89 \times e^{-x/0.09}$	0.87 **	0.05
R ₉₀₀₋₉₇₀	$\theta = 0.42 \times e^{-2.49x}$	0.21 *	0.09	$\theta = -0.01 + 1.95 \times e^{-x/0.12}$	0.92 **	0.03
S ₉₀₀₋₉₇₀	$\theta = 0.42 \times e^{-0.04x}$	0.21 *	0.09	$\theta = -0.01 + 1.86 \times e^{-x/8.82}$	0.92 **	0.04
A_Depth ₅₀₀₋₆₇₀	$\theta = e^{8.12-0.12x}$	0.06 ns	0.11	$\theta = 1.06 \times 10^6 \times e^{-10.01x}$	0.32 **	0.11
A_Area ₅₀₀₋₆₇₀	$\theta = 0.43 \times e^{-0.04x}$	0.19 *	0.09	$\theta = 2.00 \times e^{-x/6.85}$	0.87 **	0.04
A_ND ₅₀₀₋₆₇₀	$\theta = 0.09 \times e^{0.09x}$	0.16 ns	0.09	$\theta = 0.03 \times e^{0.26x}$	0.79 **	0.07
A_Depth ₇₈₀₋₉₇₀	$\theta = e^{-1.01x}$	0.31 * *	0.11	$\theta = 400.20 \times e^{-4.27x}$	0.04 ns	0.12
A_Area ₇₈₀₋₉₇₀	$\theta = 0.64 - 0.33 \times e^{x/89.43}$	0.19 *	0.09	$\theta = 2.99 \times e^{-0.12x}$	0.87 **	0.05
A_ND ₇₈₀₋₉₇₀	$\theta = 0.16 \times e^{0.02x}$	0.00 ns	0.11	$\theta = 0.01 \times e^{0.36x}$	0.89 **	0.06
A_Depth ₅₆₀₋₇₆₀	$\theta = e^{0.34-1.54x}$	0.00 ns	0.11	$\theta = 133.28 \times e^{-5.63x}$	0.24 *	0.11
A_Area ₅₆₀₋₇₆₀	$\theta = 0.43 \times e^{-0.03x}$	0.20 *	0.09	$\theta = 2.00 \times e^{-0.12x}$	0.87 **	0.07
A_ND ₅₆₀₋₇₆₀	$\theta = 0.25 - 0.95 \times e^{-x/1.65}$	0.18 ns	0.09	$\theta = 0.02 \times e^{0.39x}$	0.86 **	0.07

Note: x indicates the reflectance; ns, * and ** indicate ‘not significant’, ($p < 0.05$), and ($p < 0.01$), respectively.

Table 5. Soil moisture regression models derived from spectral feature parameters for the clay loam and sandy soils.

Spectral Feature Parameters	Clay Loam Soil ($n = 69$)	RMSE		Sandy Loam Soil ($n = 65$)	RMSE	
	Regression Equation	R ²	m ³ m ⁻³	Regression Equation	R ²	m ³ m ⁻³
R _b	$\theta = 0.79 \times e^{-16.58x}$	0.65 **	0.04	$\theta = -0.02 + 1.19 \times e^{-x/0.04}$	0.79 **	0.03
S _b	$\theta = 0.78 \times e^{-0.46x}$	0.62 **	0.04	$\theta = -0.03 + 1.05 \times e^{-x/1.78}$	0.78 **	0.03
R _y	$\theta = e^{-10.11x}$	0.73 **	0.04	$\theta = -0.01 + 1.63 \times e^{-x/0.04}$	0.82 **	0.03
S _y	$\theta = 0.36 - 2.08 \times e^{-x/1.76}$	0.76 **	0.04	$\theta = -0.01 + 1.50 \times e^{-x/1.44}$	0.81 **	0.03
R _g	$\theta = 0.89 \times e^{-12.01x}$	0.70 **	0.04	$\theta = -0.01 + 1.45 \times e^{-x/0.04}$	0.81 **	0.03
S _g	$\theta = 0.50 - 0.12 \times e^{x/5.50}$	0.73 **	0.04	$\theta = -0.02 + 1.23 \times e^{-x/2.22}$	0.80 **	0.03
R _r	$\theta = 2.83 - 2.31 \times e^{x/1.99}$	0.83 **	0.03	$\theta = 0.02 + 4.36 \times e^{-x/0.05}$	0.86 **	0.02
S _r	$\theta = 1.15 \times e^{-0.08x}$	0.80 **	0.02	$\theta = 0.01 + 3.43 \times e^{-x/4.64}$	0.86 **	0.02
R _o	$\theta = 1.10 - 0.62 \times e^{x/0.58}$	0.80 **	0.03	$\theta = 0.01 + 2.13 \times e^{-x/0.04}$	0.84 **	0.02
R ₉₀₀₋₉₇₀	$\theta = -4340.76 + 4341.29 \times e^{-x/3432.59}$	0.85 **	0.03	$\theta = 0.02 + 4.28 \times e^{-x/0.06}$	0.87 **	0.02
S ₉₀₀₋₉₇₀	$\theta = -5174.75 + 5175.28 \times e^{-x/286102.63}$	0.85 **	0.03	$\theta = 0.02 + 5.26 \times e^{-x/3.85}$	0.87 **	0.02
A_Depth ₅₀₀₋₆₇₀	$\theta = e^{-14.64 + 8.22x}$	0.46 **	0.06	$\theta = 9 \times 10^9 \times e^{-14.90x}$	0.10 ns	0.07
A_Area ₅₀₀₋₆₇₀	$\theta = 1.07 \times e^{-0.10x}$	0.77 **	0.03	$\theta = 0.01 + 2.79 \times e^{-x/3.04}$	0.85 **	0.02
A_ND ₅₀₀₋₆₇₀	$\theta = 0.34 - 1.48 \times e^{-x/3.60}$	0.81 **	0.03	$\theta = -0.10 + 0.47 \times e^{-x/11.23}$	0.85 **	0.02
A_Depth ₇₈₀₋₉₇₀	$\theta = 0.35 - 1.81 \times 10^{-17} \times e^{x/0.05}$	0.55 **	0.02	$\theta = 17.68 \times e^{-2.98x}$	0.03 ns	0.04
A_Area ₇₈₀₋₉₇₀	$\theta = -30.43 + 30.97 \times e^{-x/1975.07}$	0.84 **	0.02	$\theta = 0.24 + 6.78 \times e^{-x/4.01}$	0.86 **	0.09
A_ND ₇₈₀₋₉₇₀	$\theta = 0.26 - 1019.35 \times e^{-x/0.71}$	0.37 **	0.05	$\theta = -0.05 + 0.02 \times e^{-x/4.43}$	0.87 **	0.03
A_Depth ₅₆₀₋₇₆₀	$\theta = 0.17 + 1.63 \times 10^{-17} \times e^{-x/0.03}$	0.13 ns	0.06	$\theta = 1759.92 \times e^{8.36x}$	0.15 ns	0.07
A_Area ₅₆₀₋₇₆₀	$\theta = 1.19 - 0.71 \times e^{x/108.01}$	0.80 **	0.03	$\theta = 2.32 \times e^{-x/4.26}$	0.84 **	0.02
A_ND ₅₆₀₋₇₆₀	$\theta = 0.36 - 2.08 \times e^{-x/1.76}$	0.85 **	0.02	$\theta = -0.01 + 0.01 \times e^{x/3.47}$	0.85 **	0.03

Note: x indicates the reflectance; ns, * and ** indicate ‘not significant’, ($p < 0.05$), and ($p < 0.01$), respectively.

3.4. Artificial Neural Network Algorithm

The R² and RMSE values for the above estimated soil water contents reached a strongly significant level ($p < 0.01$), but the estimated model contained one spectrum information that other spectral information with high correlations were missing. Because ANN simulates multiple input parameters, without considering input statistical characteristics, we combined the soil spectral features and ANN in this study. Table 7 shows the results of the combined strategy to estimate θ . The R² values of each estimation model were 0.76 for sandy soil, 0.95 for loamy soil, 0.96 for clay loam soil, 0.90 for sandy loam soil, and 0.95 for the four soils altogether, respectively. The corresponding RMSE values were 0.07, 0.04, 0.02, 0.04, and 0.03 m³ m⁻³, respectively. The results demonstrated that estimating θ by combining soil spectral features with ANN was superior to estimating θ using a single spectral feature parameter. Thus the combined method improved estimation accuracy.

Applying the ANN was advantageous because it can describe nonlinear relationships and optimize the correlation between the spectral information and θ or soil organic matter data [7,14,31–33,55,56]. In summary, our results demonstrated that combining soil spectral data and an ANN algorithm could improve the accuracy of estimating soil moisture.

Table 6. Soil moisture regression models derived from spectral feature parameters.

Spectral FeatureParameters	(n = 349)		RMSE	
	Regression Equation		R ²	m ³ m ^{−3}
R _b	$\theta = e^{-0.77-7.92x}$		0.35 **	0.06
S _b	$\theta = 0.47 \times e^{-0.23x}$		0.35 **	0.06
R _y	$\theta = -0.25 + 0.64 \times e^{-x/0.48}$		0.33 **	0.07
S _y	$\theta = -0.11 + 0.52 \times e^{-x/9.40}$		0.33 **	0.07
R _g	$\theta = 0.46 \times e^{-6.00x}$		0.33 **	0.07
S _g	$\theta = -0.01 + 0.47 \times e^{-x/7.00}$		0.34 **	0.06
R _r	$\theta = -0.24 + 0.68 \times e^{-x/0.59}$		0.38 **	0.07
S _r	$\theta = -0.34 + 0.75 \times e^{-x/72.30}$		0.36 **	0.08
R _o	$\theta = -0.44 + 0.82 \times e^{-x/0.79}$		0.34 **	0.07
R ₉₀₀₋₉₇₀	$\theta = -0.05 + 0.65 \times e^{-x/0.28}$		0.48 **	0.05
S ₉₀₀₋₉₇₀	$\theta = -0.06 + 0.64 \times e^{-x/20.42}$		0.47 **	0.06
A_Depth ₅₀₀₋₆₇₀	$\theta = 0.17 + 1.61 \times 10^{36} \times e^{-x/0.62}$		0.09 ^{ns}	0.09
A_Area ₅₀₀₋₆₇₀	$\theta = -6.56 + 6.91 \times e^{-x/770.41}$		0.31 **	0.07
A_ND ₅₀₀₋₆₇₀	$\theta = 0.26 - 0.89 \times e^{-x/3.37}$		0.32 **	0.08
A_Depth ₇₈₀₋₉₇₀	$\theta = 0.89 \times e^{-0.94x}$		0.21 **	0.08
A_Area ₇₈₀₋₉₇₀	$\theta = -0.07 + 0.60 \times e^{-x/26.70}$		0.43 **	0.06
A_ND ₇₈₀₋₉₇₀	$\theta = 0.32 - 0.59 \times e^{-x/4.87}$		0.25 **	0.06
A_Depth ₅₆₀₋₇₆₀	$\theta = 0.37 \times e^{-0.59x}$		0.01 ^{ns}	0.09
A_Area ₅₆₀₋₇₆₀	$\theta = -0.82 + 1.18 \times e^{-x/133.97}$		0.33 **	0.07
A_ND ₅₆₀₋₇₆₀	$\theta = 0.27 - 1.03 \times e^{-x/2.00}$		0.36 **	0.07

Note: x indicates the reflectance; ns, * and ** indicate ‘not significant’, ($p < 0.05$), and ($p < 0.01$), respectively.

Table 7. Precision analyses for estimation models of soil moisture based on an ANN algorithm.

Soil Type	Factors	R ²	RMSE (m ³ m ^{−3})
Sandy soil	20	0.76 **	0.07
Loamy soil	20	0.95 **	0.04
Clay loam soil	20	0.96 **	0.02
Sandy loam soil	20	0.90 **	0.04
Whole	20	0.95 **	0.03

Note: x indicates the reflectance; ** indicate and ($p < 0.01$).

All spectral feature parameters were put into the ANN algorithm for estimating θ . The estimated θ based on this ANN model ($R^2 = 0.95$ and $RMSE = 0.03 \text{ m}^3 \text{ m}^{-3}$; Table 7) was consistent with the measured θ . The result suggested that the θ could be estimated based on the ANN algorithm. Neural networks consist of many nonlinear computational elements operating in parallel and linked to each other by multiplying factors [57]. Therefore, a neural network can determine the strongest relationship between multiple pieces of often complicated spectral information with target attributes without any limitations on sample distribution [7,29,33,56]. Moreover, ANN is an interesting tool that could be used to implement accurate and flexible retrieval algorithms [58].

4. Discussion

In this study, we selected the four types of soil (sand, loam, clay loam, and sandy loam soil) (Table 2). In certain soil textures, soil particles increase with the increase in soil bulk density causing less light to reflect from soil samples with macropores than from samples with micropores [1,16,19,30,41,52,54,59]. As soil moisture increases, the order of soil structures through which water is absorbed was reported as soil particle surface,

micropores, and macropores [19,38,53]. The VIS and NIR spectral regions are sensitive to θ for different soil textures under certain soil bulk densities [4,15–18,20–22,24,30].

Overall, models based on the spectral feature parameters $R_{900-970}$, $S_{900-970}$, $A_ND_{560-760}$, and R_b outperformed others in estimating soil moisture (θ) for all the sandy soil samples of different soil bulk densities. Moreover, there were significant relationships between $R_{900-970}$ and $S_{900-970}$ and θ for the loamy soils and their different soil bulk densities. The spectral feature parameters, i.e., $R_{900-970}$, $S_{900-970}$, R_r , $A_Area_{780-970}$, and $A_ND_{560-760}$, were strongly related to θ for the clay loam soils of various soil bulk densities. The strongest relationships were observed between θ and $A_Area_{500-670}$, $A_Area_{560-760}$, $A_Area_{780-970}$, $A_ND_{780-970}$, $R_{900-970}$, $S_{900-970}$, and R_r for the sandy loam soils with various soil bulk densities. Because the spectral reflectance between 760 and 970 nm is sensitive to water [1,6,15,18–21,52,60], these wavelengths were selected to estimate θ . Spectral feature parameters were more related to θ than the spectral reflectance in NIR regions were related to θ [3,5,15,19,21,25,52,61]. Our results agree with results of previous research that transforming original spectral data can significantly reduce the influence of environmental factors on spectral reflectance and improve the estimation accuracy of θ models. In this study, the spectral reflectance wavelengths that were sensitive to θ were located at the VIS and NIR regions, which is consistent with the results of numerous previous studies [18,37,39,46,50,52,60,61].

The variations in soil texture and soil organic content may cause the difference in the results of this study. The estimation accuracy of θ was affected by the clay content, soil organic matter, soil porosity, and distribution [1,19,30,51–53]. In the future, we plan to analyze and quantify the effects of clay and soil organic contents in enhancing the stability and potential applications of θ estimation models. The spectral wavelengths of the spectral feature parameters $R_{900-970}$, $S_{900-970}$, and $A_ND_{780-970}$ related to the water absorption wavelength. The accuracy of θ estimation models based on $R_{900-970}$ and $S_{900-970}$ were higher than that based on $A_ND_{780-970}$. The difference in accuracy may be caused by: (1) the spectral wavelengths of $R_{900-970}$ and $S_{900-970}$ were more sensitive to θ than that of $A_ND_{780-970}$; or (2) the strong relationships between θ and $R_{900-970}$, $S_{900-970}$, $A_Depth_{780-970}$, and $A_ND_{560-760}$ among different soil textures [12,17,25,35].

Satisfactory results of quantitative estimations of θ were achieved based on the laboratory soil spectral measurements of this study. The spectral feature parameters and ANN algorithm obtained excellent results (Tables 4–7 and Figures 5–8). The ANN algorithm performed better than spectral feature parameters for θ estimation, indicating ANN improved estimation accuracy of θ . The method that combined spectral feature parameters and ANN contained many θ -sensitive bands. Because ANN algorithms were nonlinear computational elements, they can enhance θ estimation accuracy. The RMSE value of the regression between the measured and estimated values was $0.03 \text{ m}^3 \text{ m}^{-3}$ (Table 7). Previous results have shown that soil reflectance varies with soil moisture, and these variations occur over the entire VIS, NIR, and SWIR spectra and are largely independent of the water absorption bands [11,15,16,18,20,30,39,52,59]. This ANN algorithm could be used to improve a model that is sensitive to soil moisture. The ANN can handle the effects of soil bulk density on θ estimations based on spectral feature parameters. Our laboratory results indicate that combining soil spectral feature parameters and an ANN algorithm was more accurate for estimating soil moisture by considering some of the physical properties of the soil and is supported by results of [62]. The method needs further refinement and validation before applying it to analyze satellite data to estimate θ at a regional scale in the future. However, the ANN-generated model has some shortcomings. First, spectral feature parameters of the model are used in the visible and near infrared spectra. Therefore, an ANN model is only suitable for estimating θ in areas with bare soil or low vegetation cover. Second, the model extracted spectral feature parameters near the 760- and 970-nm absorption depths, so the model needs to be improved when remote sensing is applied at a wider band. Lastly, our model was based on lab-derived soil samples that we sieved, dried, and then mixed

with distilled water to simulate field soil conditions. Thus we lacked actual field condition data. So applying the model in field is the logical next step.

5. Conclusions

In this study, various spectral feature parameters were used to determine the most accurate empirical model for soil moisture (θ) estimation based on surface soil reflectance. Reflectance data were obtained by a field portable spectroradiometer from soil samples of different soil textures with different bulk densities (ρ). The conclusions are as follows: (1) reflectance was influenced by θ , and soil reflectance was decreased with increasing θ ; (2) θ was negatively correlated to spectral feature parameters with the same ρ . The spectral feature parameters were negatively correlated to all of ρ ; (3) the spectral feature parameters $R_{900-970}$ and $S_{900-970}$ were the most sensitive to θ for four soil texture; (4) the best estimation of θ was from the model based on the combined use of spectral feature parameters and an ANN algorithm, which was more universally applicable to a wider range of soil types.

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Appendix A

Table A1. The θ regression models derived from spectral feature parameters, where the soil bulk densities were 1.40 and 1.50 g cm⁻³.

Sandy Soil	1.40 g cm ⁻³ (<i>n</i> = 24)	RMSE		1.50 g cm ⁻³ (<i>n</i> = 27)	RMSE	
	Regression Equation	R ²	m ³ m ⁻³	Regression Equation	R ²	m ³ m ⁻³
R _b	$\theta = 5.32 \times e^{-32.61x}$	0.78 **	0.04	$\theta = -0.16 + 1.37 \times e^{-x/0.15}$	0.72 **	0.06
S _b	$\theta = 4.54 \times e^{-0.87x}$	0.76 **	0.05	$\theta = -0.15 + 1.34 \times e^{-x/5.37}$	0.72 **	0.07
R _y	$\theta = 9.19 \times e^{-26.50x}$	0.81 **	0.05	$\theta = -0.18 + 1.43 \times e^{-x/0.23}$	0.68 **	0.06
S _y	$\theta = 8.23 \times e^{-0.85x}$	0.80 **	0.04	$\theta = -0.18 + 1.43 \times e^{-x/6.74}$	0.70 **	0.06
R _g	$\theta = -0.03 + 5.73 \times e^{-x/0.04}$	0.80 **	0.04	$\theta = -0.17 + 1.44 \times e^{-x/0.20}$	0.70 **	0.06
S _g	$\theta = -0.03 + 4.33 \times e^{-x/1.85}$	0.78 **	0.04	$\theta = -0.16 + 1.39 \times e^{-x/8.08}$	0.72 **	0.06
R _r	$\theta = -0.03 + 5.99 \times e^{-x/0.06}$	0.86 **	0.04	$\theta = 2.17 \times e^{-5.72x}$	0.61 **	0.06
S _r	$\theta = -0.03 + 6.24 \times e^{-x/5.66}$	0.85 **	0.04	$\theta = 2.19 \times e^{-0.06x}$	0.61 **	0.06
R _o	$\theta = -0.03 + 6.69 \times e^{-x/0.05}$	0.83 **	0.04	$\theta = 2.28 \times e^{-7.17x}$	0.64 **	0.06
R ₉₀₀₋₉₇₀	$\theta = -0.03 + 3.88 \times e^{-x/0.07}$	0.96 **	0.04	$\theta = -0.16 + 1.37 \times e^{-x/0.15}$	0.72 **	0.06
S ₉₀₀₋₉₇₀	$\theta = -0.03 + 4.15 \times e^{-x/4.79}$	0.97 **	0.04	$\theta = -0.24 + 1.33 \times e^{-x/27.37}$	0.73 **	0.05
A_Depth ₅₀₀₋₆₇₀	$\theta = 267,582.26 \times e^{-8.92x}$	0.10 ns	0.11	$\theta = 0.16 + 1.59 \times 10^{47} \times e^{-x/0.01}$	0.22 ns	0.11
A_Area ₅₀₀₋₆₇₀	$\theta = -0.26 + 0.10 \times e^{x/15.32}$	0.84 **	0.04	$\theta = e^{0.87 - 0.09x}$	0.62 **	0.06
A_ND ₅₀₀₋₆₇₀	$\theta = -0.16 + 0.04 \times e^{x/5.43}$	0.90 **	0.03	$\theta = 0.63 - 1.35 \times e^{-x/4.80}$	0.61 **	0.05
A_Depth ₇₈₀₋₉₇₀	$\theta = -701,619.63 \times e^{-1.19x}$	0.64 **	0.06	$\theta = 0.57 - 0.07 \times e^{x/1.04}$	0.50 **	0.11
A_Area ₇₈₀₋₉₇₀	$\theta = -0.03 + 5.46 \times e^{-x/5.24}$	0.86 **	0.04	$\theta = e^{0.63 - 0.06x}$	0.55 **	0.07
A_ND ₇₈₀₋₉₇₀	$\theta = 0.19 - 2.08 \times 10^8 \times e^{-x/0.32}$	0.20 ns	0.06	$\theta = 0.10 \times e^{0.15x}$	0.01 ns	0.11
A_Depth ₅₆₀₋₇₆₀	$\theta = -0.26 + 0.10 \times e^{x/5.32}$	0.01 ns	0.07	$\theta = 78.48 \times e^{-4.70x}$	0.11 ns	0.12
A_Area ₅₆₀₋₇₆₀	$\theta = -0.02 + 6.88 \times e^{-x/4.88}$	0.83 **	0.04	$\theta = e^{0.80 - 0.07x}$	0.62 **	0.06
A_ND ₅₆₀₋₇₆₀	$\theta = -0.26 + 0.10 \times e^{x/5.32}$	0.91 **	0.22	$\theta = 0.57 - 1.23 \times e^{-x/3.01}$	0.54 **	0.05

Note: *x* indicates the reflectance; ns, * and ** indicate ‘not significant’, (*p* < 0.05), and (*p* < 0.01), respectively.

Table A2. The θ regression models derived from spectral feature parameters, where the soil bulk densities were 1.60 and 1.70 g cm⁻³.

Sandy Soil	1.60 g cm ⁻³ (n = 28)	RMSE		1.70 g cm ⁻³ (n = 27)	RMSE	
	Regression Equation	R ²	m ³ m ⁻³	Regression Equation	R ²	m ³ m ⁻³
R _b	$\theta = -0.11 + 2.29 \times e^{-x/0.08}$	0.76 **	0.06	$\theta = 1.87 \times e^{-17.70x}$	0.86 **	0.04
S _b	$\theta = -0.11 + 2.11 \times e^{-x/3.14}$	0.72 **	0.05	$\theta = 1.77 \times e^{-0.48x}$	0.86 **	0.05
R _y	$\theta = -0.12 + 2.83 \times e^{-x/0.11}$	0.84 **	0.06	$\theta = 2.23 \times e^{-13.30x}$	0.87 **	0.04
S _y	$\theta = -0.12 + 2.73 \times e^{-x/3.41}$	0.82 **	0.05	$\theta = 2.15 \times e^{-0.43x}$	0.87 **	0.04
R _g	$\theta = -0.12 + 2.69 \times e^{-x/0.10}$	0.81 **	0.06	$\theta = 2.12 \times e^{-14.70x}$	0.87 **	0.04
S _g	$\theta = -0.12 + 2.38 \times e^{-x/4.45}$	0.77 **	0.06	$\theta = 1.92 \times e^{-0.33x}$	0.86 **	0.04
R _r	$\theta = -0.16 + 2.52 \times e^{-x/0.17}$	0.90 **	0.05	$\theta = 2.29 \times e^{-9.87x}$	0.87 **	0.04
S _r	$\theta = -0.15 + 3.61 \times e^{-x/16.05}$	0.90 **	0.05	$\theta = 2.29 \times e^{-0.10x}$	0.87 **	0.03
R _o	$\theta = -0.13 + 2.79 \times e^{-x/0.13}$	0.87 **	0.06	$\theta = 2.25 \times e^{-11.70x}$	0.87 **	0.04
R ₉₀₀₋₉₇₀	$\theta = -0.21 + 1.97 \times e^{-x/0.23}$	0.92 **	0.03	$\theta = -1.25 + 1.79 \times e^{-x/1.25}$	0.88 **	0.04
S ₉₀₀₋₉₇₀	$\theta = -0.20 + 2.06 \times e^{-x/15.00}$	0.92 **	0.03	$\theta = -1.29 + 1.83 \times e^{-x/88.31}$	0.88 **	0.04
A_Depth ₅₀₀₋₆₇₀	$\theta = 0.85 \times e^{-0.92x}$	0.00 ^{ns}	0.13	$\theta = 694,617,504.34 \times e^{-13.85x}$	0.19 ^{ns}	0.12
A_Area ₅₀₀₋₆₇₀	$\theta = -0.13 + 3.01 \times e^{-x/10.42}$	0.89 **	0.04	$\theta = 2.43 \times e^{-0.14x}$	0.87 **	0.03
A_ND ₅₀₀₋₆₇₀	$\theta = -2.83 + 2.38 \times e^{x/28.76}$	0.19 ^{ns}	0.03	$\theta = -1.25 + 1.79 \times e^{-x/1.25}$	0.84 **	0.04
A_Depth ₇₈₀₋₉₇₀	$\theta = 1.34 \times 10^{-16} \times e^{18.13x}$	0.05 ^{ns}	0.12	$\theta = 0.36 - 1.54 \times e^{-x/3.86}$	0.84 **	0.04
A_Area ₇₈₀₋₉₇₀	$\theta = 4.87 \times e^{-0.11x}$	0.88 **	0.04	$\theta = 2.14 \times e^{-0.11x}$	0.87 **	0.03
A_ND ₇₈₀₋₉₇₀	$\theta = 122.37 - 122.82 \times e^{-x/1225.62}$	0.74 **	0.08	$\theta = 0.02 \times e^{-0.35x}$	0.33 ^{ns}	0.08
A_Depth ₅₆₀₋₇₆₀	$\theta = 8.32 \times 10^{-100} \times e^{106.81x}$	ns	0.23	$\theta = 91.08 \times e^{48.10x}$	0.00 ^{ns}	0.12
A_Area ₅₆₀₋₇₆₀	$\theta = 5.35 \times e^{-0.12x}$	0.85 **	0.04	$\theta = 2.30 \times e^{-0.11x}$	0.87 **	0.02
A_ND ₅₆₀₋₇₆₀	$\theta = 2.57 - 3.17 \times e^{-x/15.51}$	0.94 **	0.03	$\theta = 0.03 \times e^{0.27x}$	0.73 **	0.07

Note: x indicates the reflectance; ns, * and ** indicate ‘not significant’, ($p < 0.05$), and ($p < 0.01$), respectively.

Table A3. The θ regression models derived from spectral feature parameters, where the soil bulk densities were 1.20 and 1.30 g cm⁻³.

Loamy Soil	1.20 g cm ⁻³ (n = 27)	RMSE		1.30 g cm ⁻³ (n = 25)	RMSE	
	Regression Equation	R ²	m ³ m ⁻³	Regression Equation	R ²	m ³ m ⁻³
R _b	$\theta = -0.01 + 1.77 \times e^{-x/0.05}$	0.92 **	0.04	$\theta = -0.07 + 1.23 \times e^{-x/0.08}$	0.92 **	0.06
S _b	$\theta = -0.02 + 1.57 \times e^{-x/0.88}$	0.92 **	0.05	$\theta = -0.08 + 1.16 \times e^{-x/2.85}$	0.91 **	0.04
R _y	$\theta = -0.01 + 2.22 \times e^{-x/0.06}$	0.92 **	0.05	$\theta = -0.07 + 1.35 \times e^{-x/0.10}$	0.93 **	0.04
S _y	$\theta = -0.01 + 2.12 \times e^{-x/1.97}$	0.92 **	0.04	$\theta = -0.07 + 1.33 \times e^{-x/3.08}$	0.93 **	0.04
R _g	$\theta = -0.01 + 2.08 \times e^{-x/0.06}$	0.92 **	0.04	$\theta = -0.07 + 1.32 \times e^{-x/0.09}$	0.92 **	0.04
S _g	$\theta = -0.01 + 1.83 \times e^{-x/2.61}$	0.92 **	0.04	$\theta = -0.07 + 1.25 \times e^{-x/4.02}$	0.92 **	0.05
R _r	$\theta = -9.25 \times 10^{-4} + 2.65 \times e^{-x/0.09}$	0.92 **	0.03	$\theta = -0.02 + 2.27 \times e^{-x/0.10}$	0.92 **	0.04
S _r	$\theta = -5.11 \times 10^{-4} + 2.61 \times e^{-x/8.55}$	0.92 **	0.03	$\theta = -0.03 + 1.90 \times e^{-x/10.75}$	0.93 **	0.05
R _o	$\theta = 2.37 \times e^{-x/0.07}$	0.92 **	0.04	$\theta = -0.05 + 1.51 \times e^{-x/0.10}$	0.93 **	0.04
R ₉₀₀₋₉₇₀	$\theta = -0.01 + 1.96 \times e^{-x/0.12}$	0.96 **	0.02	$\theta = -0.02 + 1.89 \times e^{-x/0.13}$	0.95 **	0.03
S ₉₀₀₋₉₇₀	$\theta = -0.01 + 1.87 \times e^{-x/8.39}$	0.96 **	0.02	$\theta = -0.04 + 1.65 \times e^{-x/9.65}$	0.96 **	0.03
A_Depth ₅₀₀₋₆₇₀	$\theta = 4.37 \times 10^7 \times e^{-12.54x}$	0.31 ^{ns}	0.11	$\theta = 787.28 \times e^{-5.29x}$	0.06 ^{ns}	0.1
A_Area ₅₀₀₋₆₇₀	$\theta = 2.55 \times e^{-0.17x}$	0.91 **	0.03	$\theta = 1.91 \times e^{-0.15x/0.13}$	0.93 **	0.04
A_ND ₅₀₀₋₆₇₀	$\theta = e^{-4.19+0.24x}$	0.85 **	0.04	$\theta = 0.03 \times e^{0.17x}$	0.81 **	0.06
A_Depth ₇₈₀₋₉₇₀	$\theta = e^{8.28-5.66x}$	0.04 ^{ns}	0.12	$\theta = 1060.21 \times e^{-4.78x}$	0.12 ^{ns}	0.13
A_Area ₇₈₀₋₉₇₀	$\theta = 2.66 \times e^{-0.12x}$	0.90 **	0.05	$\theta = 4.02 \times e^{-0.14x}$	0.90 **	0.03
A_ND ₇₈₀₋₉₇₀	$\theta = 4621.17 - 4621.39 \times e^{-x/87,464.58}$	0.88 **	0.04	$\theta = e^{0.43x}$	0.89 **	0.03
A_Depth ₅₆₀₋₇₆₀	$\theta = 0.05 + 841.00 \times e^{-x/0.13}$	0.09 ^{ns}	0.2	$\theta = 10.38 \times e^{-3.35x}$	0.08 ^{ns}	0.11
A_Area ₅₆₀₋₇₆₀	$\theta = 2.50 \times e^{-x/7.18}$	0.92 **	0.04	$\theta = 1.87 \times e^{-0.12x}$	0.93 **	0.03
A_ND ₅₆₀₋₇₆₀	$\theta = e^{-4.22+0.39x}$	0.86 **	0.04	$\theta = 0.02 \times e^{0.38x}$	0.91 **	0.05

Note: x indicates the reflectance; ns, * and ** indicate ‘not significant’, ($p < 0.05$), and ($p < 0.01$), respectively.

Table A4. The θ regression models derived from spectral feature parameters, where the soil bulk densities were 1.40 and 1.50 g cm⁻³.

Loamy Soil	1.40 g cm ⁻³ (n = 29)	RMSE		1.50 g cm ⁻³ (n = 32)	RMSE	
	Regression Equation	R ²	m ³ m ⁻³	Regression Equation	R ²	m ³ m ⁻³
R _b	$\theta = 0.01 + 1.65 \times e^{-x/0.05}$	0.88 **	0.05	$\theta = 2.17 \times e^{-19.47x}$	0.87 **	0.03
S _b	$\theta = 1.42 \times e^{-0.48x}$	0.88 **	0.04	$\theta = 1.86 \times e^{-0.51x}$	0.87 **	0.04
R _y	$\theta = 2.06 \times e^{-14.43x}$	0.87 **	0.03	$\theta = 3.00 \times e^{-15.70x}$	0.87 **	0.03
S _y	$\theta = 1.94 \times e^{-0.46x}$	0.87 **	0.03	$\theta = 2.82 \times e^{-0.51x}$	0.87 **	0.03
R _g	$\theta = 1.89 \times e^{-15.63x}$	0.87 **	0.03	$\theta = 2.73 \times e^{-17.00x}$	0.87 **	0.03
S _g	$\theta = 0.01 + 1.72 \times e^{-x/2.77}$	0.88 **	0.04	$\theta = 2.27 \times e^{-0.37x}$	0.87 **	0.03
R _r	$\theta = -0.04 + 5.12 \times e^{-x/0.07}$	0.85 **	0.1	$\theta = 2.78 \times e^{-9.81x}$	0.88 **	0.05
S _r	$\theta = 0.03 + 4.33 \times e^{-x/7.06}$	0.86 **	0.03	$\theta = 2.82 \times e^{-0.11x}$	0.87 **	0.04
R _o	$\theta = 0.03 + 3.05 \times e^{-x/10.07}$	0.87 **	0.04	$\theta = 2.85 \times e^{-13.10x}$	0.87 **	0.03
R ₉₀₀₋₉₇₀	$\theta = -0.03 + 2.99 \times e^{-x/0.10}$	0.92 **	0.03	$\theta = 0.03 + 5.95 \times e^{-x/5.54}$	0.92 **	0.03
S ₉₀₀₋₉₇₀	$\theta = -0.03 + 3.51 \times e^{-x/6.29}$	0.92 **	0.03	$\theta = 0.03 + 5.18 \times e^{-x/0.08}$	0.92 **	0.03
A_Depth ₅₀₀₋₆₇₀	$\theta = 0.14 + 7.94 \times 10^{28} \times e^{-x/0.02}$	0.45 *	0.17	$\theta = 5.90 \times 10^6 \times e^{-11.06x}$	0.32 ns	0.17
A_Area ₅₀₀₋₆₇₀	$\theta = 0.03 + 3.97 \times e^{-x/4.83}$	0.86 **	0.03	$\theta = 2.92 \times e^{-0.16x}$	0.87 **	0.04
A_ND ₅₀₀₋₆₇₀	$\theta = -0.03 + 0.02 \times e^{x/4.39}$	0.86 **	0.05	$\theta = -0.05 + 0.03 \times e^{-x/2.67}$	0.89 **	0.05
A_Depth ₇₈₀₋₉₇₀	$\theta = 400.20 \times e^{-4.27x}$	0.04 ns	0.13	$\theta = 0.18 - 9.99 \times 10^{210} \times e^{-x/0.003}$	0.07 ns	0.11
A_Area ₇₈₀₋₉₇₀	$\theta = 0.05 + 8.30 \times e^{-x/5.55}$	0.84 **	0.03	$\theta = 0.04 + 6.44 \times e^{-x/6.31}$	0.87 **	0.03
A_ND ₇₈₀₋₉₇₀	$\theta = 0.02 + 0.004 \times e^{x/12.24}$	0.85 **	0.04	$\theta = -0.09 + 0.05 \times e^{x/4.40}$	0.90 **	0.02
A_Depth ₅₆₀₋₇₆₀	$\theta = 0.13 + 2.57 \times 10^8 \times e^{-x/0.05}$	0.34 ns	0.13	$\theta = e^{5.47-6.00x}$	0.24 ns	0.12
A_Area ₅₆₀₋₇₆₀	$\theta = 0.03 + 3.41 \times e^{-x/6.34}$	0.86 **	0.03	$\theta = 0.04 + 9.62 \times e^{-x/4.84}$	0.87 **	0.03
A_ND ₅₆₀₋₇₆₀	$\theta = -0.01 + 0.01 \times e^{x/2.29}$	0.86 **	0.13	$\theta = -0.05 + 0.03 \times e^{x/2.67}$	0.89 **	0.04

Note: x indicates the reflectance; ns, * and ** indicate 'not significant', ($p < 0.05$), and ($p < 0.01$), respectively.

Table A5. The θ regression models derived from spectral feature parameters, where the soil bulk densities were 1.30 and 1.40 g cm⁻³.

Clay Loam Soil	1.30 g cm ⁻³ (n = 15)	RMSE		1.40 g cm ⁻³ (n = 15)	RMSE	
	Regression Equation	R ²	m ³ m ⁻³	Regression Equation	R ²	m ³ m ⁻³
R _b	$\theta = 0.23 - 0.01 \times e^{x/0.04}$	0.86 **	0.05	$\theta = 0.78 \times e^{-18.73x}$	0.80 **	0.05
S _b	$\theta = 1.56 \times e^{-0.93x}$	0.68 **	0.04	$\theta = 0.31 - 0.02 \times e^{-x/1.58}$	0.84 **	0.05
R _y	$\theta = 1.08 \times e^{-13.22x}$	0.90 **	0.01	$\theta = 0.35 - 0.003 \times e^{x/0.10}$	0.86 **	0.04
S _y	$\theta = 0.97 \times e^{-0.46x}$	0.88 **	0.01	$\theta = 0.34 - 0.02 \times e^{x/2.68}$	0.86 **	0.04
R _g	$\theta = 0.28 - 0.03 \times e^{x/0.08}$	0.88 **	0.07	$\theta = 0.33 - 0.02 \times e^{x/0.07}$	0.86 **	0.04
S _g	$\theta = 0.77 \times e^{-0.39x}$	0.83 **	0.03	$\theta = 0.80 \times e^{-0.34x}$	0.80 **	0.05
R _r	$\theta = 0.54 - 0.18 \times e^{x/0.34}$	0.95 **	0.01	$\theta = 0.45 - 0.08 \times e^{x/0.21}$	0.90 **	0.04
S _r	$\theta = 0.65 - 0.28 \times e^{x/42.87}$	0.94 **	0.01	$\theta = 1.11 \times e^{-0.08x}$	0.86 **	0.04
R _o	$\theta = 1.92 - 1.52 \times e^{x/1.36}$	0.93 **	0.01	$\theta = 0.41 - 0.06 \times e^{x/0.16}$	0.88 **	0.04
R ₉₀₀₋₉₇₀	$\theta = 0.43 - 0.09 \times e^{x/0.25}$	0.95 **	0.01	$\theta = 1.03 \times e^{-7.09x}$	0.86 **	0.04
S ₉₀₀₋₉₇₀	$\theta = 0.46 - 0.12 \times e^{x/19.72}$	0.95 **	0.01	$\theta = 1.03 \times e^{-0.10x}$	0.86 **	0.04
A_Depth ₅₀₀₋₆₇₀	$\theta = 10^{-6} \times e^{7.02x}$	0.05 ns	0.15	$\theta = 10^{-6} \times e^{7.41x}$	0.22 ns	0.1
A_Area ₅₀₀₋₆₇₀	$\theta = 1.45 - 1.06 \times e^{x/87.47}$	0.93 **	0.01	$\theta = 0.39 - 0.05 \times e^{x/12.58}$	0.88 **	0.04
A_ND ₅₀₀₋₆₇₀	$\theta = 0.004 \times e^{0.33x}$	0.54 *	0.09	$\theta = 0.30 - 1.92 \times e^{-x/2.99}$	0.87 **	0.04
A_Depth ₇₈₀₋₉₇₀	$\theta = 10^{21} \times e^{-26.90x}$	0.29 ns	0.14	$\theta = 0.31 - 1.18 \times 10^{-18} \times e^{x/0.05}$	0.83 **	0.07
A_Area ₇₈₀₋₉₇₀	$\theta = 0.52 - 0.17 \times e^{x/27.73}$	0.94 **	0.01	$\theta = 0.47 - 0.09 \times e^{x/19.13}$	0.91 **	0.04
A_ND ₇₈₀₋₉₇₀	$\theta = 0.003 \times e^{x/0.37}$	0.52 *	0.12	$\theta = 0.23 - 265,093.37 \times e^{-x/0.46}$	0.64 **	0.08
A_Depth ₅₆₀₋₇₆₀	$\theta = 179.20 \times e^{-7.77x}$	0.36 ns	0.13	$\theta = 161.50 \times e^{-7.13x}$	0.27 ns	0.13
A_Area ₅₆₀₋₇₆₀	$\theta = 1.18 - 0.79 \times e^{x/82.95}$	0.93 **	0.01	$\theta = 0.41 - 0.06 \times e^{x/16.53}$	0.89 **	0.04
A_ND ₅₆₀₋₇₆₀	$\theta = 0.003 \times e^{0.09x}$	0.42 ns	0.1	$\theta = 0.01 \times e^{0.55x}$	0.50 *	0.04

Note: x indicates the reflectance; ns, * and ** indicate 'not significant', ($p < 0.05$), and ($p < 0.01$), respectively.

Table A6. The θ regression models derived from spectral feature parameters, where the soil bulk densities were 1.50 and 1.60 g cm⁻³.

Clay Loam Soil	1.50 g cm ⁻³ (n = 22)	RMSE		1.60 g cm ⁻³ (n = 19)	RMSE	
	Regression Equation	R ²	m ³ m ⁻³	Regression Equation	R ²	m ³ m ⁻³
R _b	$\theta = 0.93 - 0.41 \times e^{x/0.18}$	0.78 **	0.07	$\theta = -0.20 + 1.01 \times e^{-x/0.10}$	0.91 **	0.06
S _b	$\theta = 0.91 - 0.38 \times e^{x/6.05}$	0.78 **	0.08	$\theta = -0.17 + 1.06 \times e^{-x/2.94}$	0.90 **	0.06
R _y	$\theta = 1.25 \times e^{-10.07x}$	0.74 **	0.07	$\theta = -0.96 + 1.60 \times e^{-x/0.56}$	0.92 **	0.05
S _y	$\theta = 1.25 \times e^{-0.36x}$	0.74 **	0.07	$\theta = -0.53 + 1.20 \times e^{-x/9.69}$	0.91 **	0.06
R _g	$\theta = 0.73 - 0.23 \times e^{x/0.20}$	0.79 **	0.07	$\theta = -0.41 + 1.11 \times e^{-x/0.23}$	0.92 **	0.06
S _g	$\theta = 0.85 - 0.34 \times e^{x/9.10}$	0.78 **	0.07	$\theta = -0.22 + 1.02 \times e^{-x/5.60}$	0.91 **	0.06
R _r	$\theta = 1.19 \times e^{-6.86x}$	0.78 **	0.04	$\theta = 1.13 \times e^{-7.24x}$	0.90 **	0.04
S _r	$\theta = 0.51 - 0.06 \times e^{x/18.64}$	0.84 **	0.05	$\theta = 1.16 \times e^{-0.08x}$	0.90 **	0.05
R _o	$\theta = 1.22 \times e^{-8.41x}$	0.76 **	0.05	$\theta = -7970.73 + 7971.29 \times e^{-x/4692.96}$	0.94 **	0.06
R ₉₀₀₋₉₇₀	$\theta = 1.09 \times e^{-6.48x}$	0.80 **	0.03	$\theta = 0.98 \times e^{-6.50x}$	0.90 **	0.03
S ₉₀₀₋₉₇₀	$\theta = 1.09 \times e^{-0.09x}$	0.80 **	0.04	$\theta = 0.43 - 0.09 \times e^{x/0.25}$	0.94 **	0.04
A_Depth ₅₀₀₋₆₇₀	$\theta = 4 \times 10^{-13} \times e^{16.58x}$	0.42 *	0.13	$\theta = e^{-13.65+7.60x}$	0.42 ns	0.08
A_Area ₅₀₀₋₆₇₀	$\theta = 0.53 - 0.08 \times e^{x/15.42}$	0.82 **	0.05	$\theta = 1.83 - 1.30 \times e^{x/85.28}$	0.93 **	0.05
A_ND ₅₀₀₋₆₇₀	$\theta = 0.36 - 4.11 \times e^{-x/2.17}$	0.84 **	0.06	$\theta = 0.36 - 1.68 \times e^{-x/3.44}$	0.92 **	0.05
A_Depth ₇₈₀₋₉₇₀	$\theta = 2.80 \times e^{-2.02x}$	0.48 *	0.12	$\theta = 0.34 - 1.94 \times 10^{-18} \times e^{x/0.05}$	0.79 **	0.08
A_Area ₇₈₀₋₉₇₀	$\theta = 1.11 \times e^{-0.08x}$	0.79 **	0.04	$\theta = 1.02 \times e^{-0.08x}$	0.90 **	0.03
A_ND ₇₈₀₋₉₇₀	$\theta = 0.01 \times e^{0.39x}$	0.16 ns	0.29	$\theta = 0.29 - 1556.97 \times e^{-x/0.69}$	0.69 **	0.08
A_Depth ₅₆₀₋₇₆₀	$\theta = 0.12 + 7.17 \times 10^{-12} \times e^{x/0.05}$	0.16 ns	0.1	$\theta = 0.15 + 1.02 \times 10^{-29} \times e^{x/0.02}$	0.31 ns	0.11
A_Area ₅₆₀₋₇₆₀	$\theta = 1.21 \times e^{-0.08x}$	0.76 **	0.05	$\theta = 1.77 - 1.24 \times e^{x/99.08}$	0.94 **	0.05
A_ND ₅₆₀₋₇₆₀	$\theta = 0.36 - 10.09 \times e^{-x/0.95}$	0.87 **	0.05	$\theta = 0.34 - 4.25 \times e^{-x/1.26}$	0.94 **	0.05

Note: x indicates the reflectance; ns, * and ** indicate 'not significant', ($p < 0.05$), and ($p < 0.01$), respectively.

Table A7. The θ regression models derived from spectral feature parameters, where the soil bulk densities were 1.30 and 1.40 g cm⁻³.

Sandy Loam Soil	1.30 g cm ⁻³ (n = 15)	RMSE		1.40 g cm ⁻³ (n = 14)	RMSE	
	Regression Equation	R ²	m ³ m ⁻³	Regression Equation	R ²	m ³ m ⁻³
R _b	$\theta = 1.69 \times e^{-x/0.03}$	0.89 **	0.05	$\theta = 2.98 \times e^{-38.70x}$	0.80 **	0.05
S _b	$\theta = -0.01 + 1.45 \times e^{-x/1.32}$	0.89 **	0.05	$\theta = 2.84 \times e^{-1.03x}$	0.80 **	0.05
R _y	$\theta = 0.01 + 2.61 \times e^{-x/0.03}$	0.90 **	0.06	$\theta = 3.47 \times e^{-32.20x}$	0.81 **	0.05
S _y	$\theta = 0.01 + 2.30 \times e^{-x/1.10}$	0.90 **	0.05	$\theta = 3.34 \times e^{-1.02x}$	0.81 **	0.05
R _g	$\theta = 3.07 \times e^{-34.00x}$	0.84 **	0.05	$\theta = 3.33 \times e^{-34.60x}$	0.81 **	0.05
S _g	$\theta = 1.78 \times e^{-x/1.67}$	0.89 **	0.05	$\theta = 3.07 \times e^{-0.74x}$	0.81 **	0.05
R _r	$\theta = 0.03 + 18.83 \times e^{-x/0.03}$	0.90 **	0.04	$\theta = 0.01 + 4.00 \times e^{-x/0.05}$	0.90 **	0.06
S _r	$\theta = 0.03 + 9.98 \times e^{-x/3.17}$	0.91 **	0.04	$\theta = 2.99 \times e^{-x/4.92}$	0.88 **	0.05
R _o	$\theta = 0.02 + 3.98 \times e^{-x/0.03}$	0.91 **	0.05	$\theta = -0.02 + 1.75 \times e^{-x/0.05}$	0.84 **	0.05
R ₉₀₀₋₉₇₀	$\theta = 0.04 + 49.54 \times e^{-x/0.03}$	0.91 **	0.05	$\theta = 4.62 \times e^{-16.60x}$	0.80 **	0.05
S ₉₀₀₋₉₇₀	$\theta = 0.04 + 60.26 \times e^{-x/2.07}$	0.90 **	0.04	$\theta = 4.74 \times e^{-0.24x}$	0.80 **	0.04
A_Depth ₅₀₀₋₆₇₀	$\theta = 10^9 \times e^{-13.60x}$	0.14 ns	0.11	$\theta = 2 \times 10^7 \times e^{-11.30x}$	0.14 ns	0.11
A_Area ₅₀₀₋₆₇₀	$\theta = 0.02 + 5.88 \times e^{-x/2.23}$	0.91 **	0.04	$\theta = 2.27 \times e^{-x/3.38}$	0.86 **	0.05
A_ND ₅₀₀₋₆₇₀	$\theta = 0.001 \times e^{0.21x}$	0.85 **	0.03	$\theta = -0.13 + 0.06 \times e^{x/12.37}$	0.88 **	0.05
A_Depth ₇₈₀₋₉₇₀	$\theta = 5 \times 10^8 \times e^{-13.90x}$	0.08 ns	0.16	$\theta = 15.36 \times e^{-3.02x}$	0.01 ns	0.12
A_Area ₇₈₀₋₉₇₀	$\theta = 0.04 + 63.34 \times e^{-x/2.33}$	0.89 **	0.04	$\theta = 0.02 + 8.49 \times e^{-x/3.73}$	0.91 **	0.05
A_ND ₇₈₀₋₉₇₀	$\theta = 0.03 + 1.86 \times 10^{-4} \times e^{x/1.69}$	0.80 **	0.02	$\theta = -0.02 + 0.01 \times e^{x/3.55}$	0.94 **	0.05
A_Depth ₅₆₀₋₇₆₀	$\theta = 0.14 + 2.54 \times 10^{10} \times e^{x/0.04}$	0.22 ns	0.12	$\theta = 19.60 \times e^{-4.34x}$	0.06 ns	0.12
A_Area ₅₆₀₋₇₆₀	$\theta = 0.02 + 4.55 \times e^{-x/3.13}$	0.91 **	0.04	$\theta = -0.01 + 1.90 \times e^{-x/4.79}$	0.85 **	0.05
A_ND ₅₆₀₋₇₆₀	$\theta = 0.04 + 9.30 \times 10^{-5} \times e^{x/1.57}$	0.78 **	0.03	$\theta = 0.01 + 0.04 \times e^{-x/2.84}$	0.91 **	0.05

Note: x indicates the reflectance; ns, * and ** indicate 'not significant', ($p < 0.05$), and ($p < 0.01$), respectively.

Table A8. The θ regression models derived from spectral feature parameters, where the soil bulk densities were 1.50 and 1.60 g cm⁻³.

Sandy Loam	1.50 g cm ⁻³ (n = 17)	RMSE		1.60 g cm ⁻³ (n = 22)	RMSE	
	Regression Equation	R ²	m ³ m ⁻³	Regression Equation	R ²	m ³ m ⁻³
R _b	$\theta = 1.24 \times e^{-24.70x}$	0.86 **	0.03	$\theta = 2.83 \times e^{-34.60x}$	0.88 **	0.05
S _b	$\theta = 1.24 \times e^{-0.66x}$	0.86 **	0.04	$\theta = 2.81 \times e^{-0.92x}$	0.88 **	0.04
R _y	$\theta = 1.28 \times e^{-20.10x}$	0.88 **	0.03	$\theta = 0.02 + 24.10 \times e^{-x/0.02}$	0.90 **	0.04
S _y	$\theta = 1.28 \times e^{-0.64x}$	0.88 **	0.03	$\theta = 0.02 + 18.89 \times e^{-x/0.63}$	0.89 **	0.04
R _g	$\theta = 1.28 \times e^{-21.70x}$	0.88 **	0.03	$\theta = 0.02 + 16.15 \times e^{-x/0.02}$	0.88 **	0.04
S _g	$\theta = 1.25 \times e^{-0.47x}$	0.87 **	0.04	$\theta = 2.89 \times e^{-30.50x}$	0.88 **	0.02
R _r	$\theta = 1.46 \times e^{-13.00x}$	0.91 **	0.03	$\theta = 0.03 + 17.77 \times e^{-x/0.03}$	0.89 **	0.05
S _r	$\theta = 1.39 \times e^{-0.14x}$	0.91 **	0.03	$\theta = 0.03 + 27.49 \times e^{-x/2.74}$	0.90 **	0.04
R _o	$\theta = 1.29 \times e^{-17.30x}$	0.90 **	0.03	$\theta = 0.03 + 36.88 \times e^{-x/0.02}$	0.91 **	0.04
R ₉₀₀₋₉₇₀	$\theta = 1.62 \times e^{-10.70x}$	0.93 **	0.03	$\theta = 0.02 + 5.37 \times e^{-x/0.06}$	0.89 **	0.05
S ₉₀₀₋₉₇₀	$\theta = 1.57 \times e^{-0.15x}$	0.93 **	0.04	$\theta = 0.02 + 6.79 \times e^{-x/3.74}$	0.89 **	0.05
A_Depth ₅₀₀₋₆₇₀	$\theta = 7 \times 10^{-5} \times e^{4.52x}$	0.04 ns	0.11	$\theta = 1037.70 \times e^{-5.42x}$	0.02 ns	0.12
A_Area ₅₀₀₋₆₇₀	$\theta = 1.30 \times e^{-0.22x}$	0.90 **	0.04	$\theta = 0.03 + 35.50 \times e^{-x/1.57}$	0.90 **	0.04
A_ND ₅₀₀₋₆₇₀	$\theta = 0.01 \times e^{0.16x}$	0.93 **	0.08	$\theta = 0.001 \times e^{-0.48x}$	0.89 **	0.21
A_Depth ₇₈₀₋₉₇₀	$\theta = 647.50 \times e^{-5.30x}$	0.04 ns	0.09	$\theta = 10^{12} \times e^{-19.10x}$	0.25 ns	0.13
A_Area ₇₈₀₋₉₇₀	$\theta = 1.54 \times e^{-0.13x}$	0.92 **	0.05	$\theta = 0.02 + 10.10 \times e^{-x/3.76}$	0.89 **	0.04
A_ND ₇₈₀₋₉₇₀	$\theta = 0.01 \times e^{0.32x}$	0.95 **	0.14	$\theta = -0.09 + 0.03 \times e^{-x/4.89}$	0.89 **	0.05
A_Depth ₅₆₀₋₇₆₀	$\theta = 0.15 + 8.56 \times 10^{-61} \times e^{x/0.01}$	0.01 ns	0.11	$\theta = 116.30 \times e^{-5.94x}$	0.07 ns	0.12
A_Area ₅₆₀₋₇₆₀	$\theta = 1.28 \times e^{-0.17x}$	0.90 **	0.04	$\theta = 0.03 + 42.49 \times e^{-x/1.98}$	0.91 **	0.04
A_ND ₅₆₀₋₇₆₀	$\theta = 0.01 \times e^{0.30x}$	0.94 **	0.09	$\theta = 0.04x - 0.20$	0.87 **	0.05

Note: x indicates the reflectance; ns, * and ** indicate 'not significant', ($p < 0.05$), and ($p < 0.01$), respectively.

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