Study on soil moisture content in soybean root zone based on UAV multispectral remote sensing

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Abstract: Timely acquisition of soil moisture in the root zone of farmland crops is the basis and key to achieve precise irrigation. In this study, based on UAV multi-spectral remote sensing technology, soybeans in Northwest China were selected as the research object, and ten vegetation indices with the best correlation with soybean soil moisture content were selected. Random Forest (RF), Extreme Learning Machine (ELM) and Back propagation neural network (BPNN) were used to construct the estimation model of soybean soil moisture content, and the model was verified. The results showed that the correlation between each spectral index and soil moisture content was high, and the correlation between spectral index OSAVI and soybean soil moisture content was the highest, which was 0.740. The change of OSAVI could monitor the change of soybean soil moisture content in real time. The accuracy of soybean LAI and aboveground biomass prediction model based on RF model was significantly higher than that of ELM and BP model. The R^2, RMSE and MRE of soil moisture content monitoring model validation set were 0.803, 0.011 and 4.847, respectively. The results of this study can provide a theoretical basis for the application of UAV multi-spectral remote sensing in crop soil moisture monitoring, and provide a new way for rapid and accurate monitoring of farmland soil moisture and implementation of precision irrigation.

Keywords: soybean; soil moisture content; UAV remote sensing; vegetation index; machine learning
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1 Introduction

Soil moisture content is a key parameter of energy balance and hydrological cycle between land surface and atmosphere, and also an important factor restricting crop growth and development in arid and semi-arid areas[1]. Timely and accurate acquisition of soil moisture content is the basis and key to monitor crop growth, guide irrigation decisions and achieve precision agriculture. Remote sensing technology has a wide application prospect in soil moisture content monitoring because of its high efficiency and accuracy[2-5].

At present, there are two methods to obtain crop soil moisture content, namely direct measurement method[6] and indirect measurement method[7]. The accuracy of the former is higher than that of the latter, but the direct measurement method requires destructive sampling of crops, which is not only time-consuming and laborious, but also the sample is not necessarily representative, so the method has certain limitations. In contrast, the indirect measurement method is a method that combines crop spectral information with field measured data and estimates crop soil moisture content through models, which is fast and efficient[8]. In recent years, UAV multi-spectral remote sensing system has made great progress in monitoring water stress of farmland crops with its advantages of low cost, convenient acquisition, high timeliness and high spatial and temporal resolution[9]. Bian et al. (2019)[10] used UAV equipped with thermal infrared and multi-spectral sensors to diagnose the water stress status of cotton through Crop water stress index (CWSI) and various vegetation indices. Chen et al.[11] inverted the water stress index-transpiration rate and stomatal conductance by using the spectral reflectance of vegetation through the multi-spectral remote sensing images of canopy UAV at different times of cotton bud stage. Zhang et al.[12] used the six-rotor UAV equipped with MCA multi-spectral sensor to complete the inversion of bare soil moisture content, the inversion accuracy was high, and the determination coefficient was above 0.7.

In addition, there are large differences between spectral reflectance and vegetation index in different canopy layers, and there are also strong collinearity problems[13]. Therefore, screening sensitive spectral indices is of great significance for soil moisture monitoring[14]. The relationship between soil moisture content and vegetation spectrum is complex, and the classical regression method is difficult to achieve unbiased and effective parameter estimation. The machine learning method has great advantages in solving the complex relationship problems such as nonlinearity and heteroscedasticity, and is a hot spot in the field of agricultural remote sensing modeling and inversion[15]. Therefore, in this study, soybean in Northwest China was taken as the research object. The multi-spectral data of soybean in the field were obtained by UAV, and the relationship between vegetation index and soil moisture content in each growth period was comprehensively analyzed. Then, three machine learning

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methods, Random Forest (RF), Back propagation neural network (BPNN) and Extreme learning machine (ELM), were used to establish quantitative models. The effects of different machine learning methods on the accuracy of soybean soil moisture estimation model were discussed, in order to provide a theoretical reference for more accurate and rapid prediction of soybean soil moisture content.

2 Materials and methods

2.1. Research Area and Test Design

In the present study, a soybean field experiment was conducted at the Institute of Water-saving Agriculture in Arid Areas of China (34°18′ N, 108°24′ E, 521 m a.s.l.) (Figure 1).

In this experiment, four mulching types were set up: straw mulching (SM), mulching with plastic film mulching (SFM), film mulching (FM) and no mulching (NM). Five nitrogen application rates were set: 0 kg/hm^2 (N0), 30 kg/hm^2 (N1), 60 kg/hm^2 (N2), 90 kg/hm^2 (N3) and 120 kg/hm^2 (N4), a total of 20 treatments.

Seven planting densities were set: 150 000 plants/hm^2 (R0), 200 000 plants/hm^2 (R1), 250 000 plants/hm^2 (R2), 300 000 plants/hm^2 (R3), 350 000 plants/hm^2 (R4), 400 000 plants/hm^2 (R5) and 450 000 plants/hm^2 (R6). The aerial photos of some test areas are shown in Figure 2.

The principle of random arrangement was adopted when setting up each treatment plot, and two replicates were set up, with a total of 27 treatments. The plot area was 3 m × 6 m = 18 m^2, and a 2 m protective belt was laid around the test area. The phosphorus and potassium fertilizers in each plot were consistent, both 30 kg/hm^2. On June 18, 2021, soybeans were sown manually according to the row spacing of 50 cm and the plant spacing of about 10 cm, and other field production management (spraying, weeding, etc.) were consistent with the local area. Soybeans are harvested on September 30 and mulch film is recovered.

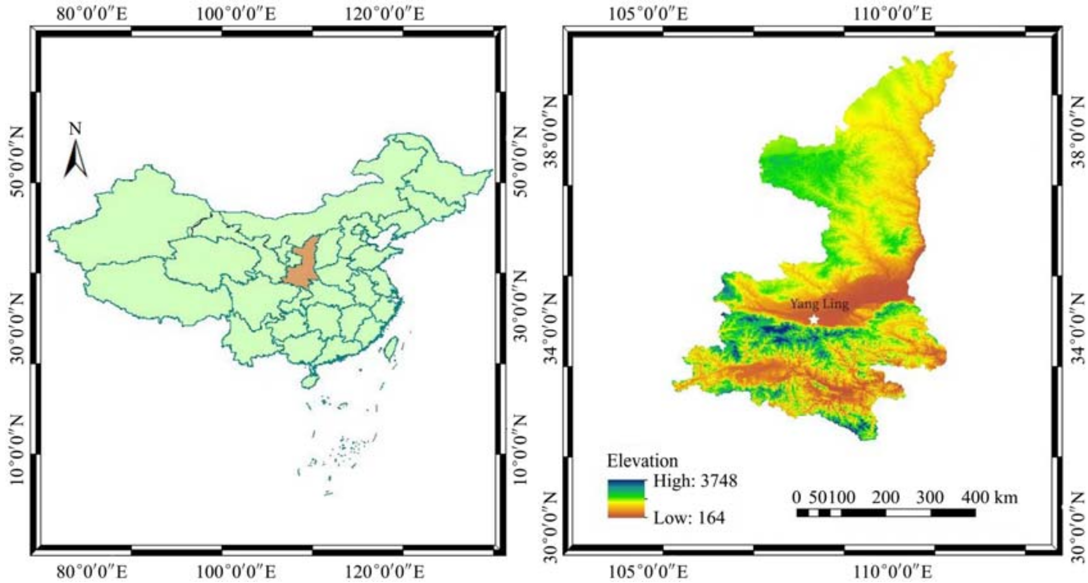


Figure 1 Study area

Figure 2 Aerial photos of some study plots

2.2 Measurements and methods

2.2.1 UAV image data acquisition and processing

The UAV remote sensing images were acquired on July 25, 2021 (four-section period, V4), August 20, 2021 (flowering period, R4) and September 5, 2021 (seed filling period, R6). The multi-spectral image data of soybean canopy were obtained by using Phantom4-M (P4M), and the UAV and multispectral lens parameters are shown in Figure 3. The device integrates 1 visible light sensor channel and 5 multispectral sensor channels (blue, green, red, red edge and near infrared), and can obtain 6 images at a time. Each image has a resolution of more than 2 million pixels, a maximum flight speed of 14 m/s, and a maximum endurance time of 27 min. With the TimeSync time synchronization system, centimeter-level positioning accuracy can be obtained. In addition, the top of the P4M integrates light intensity sensors, which can capture solar irradiance data for image illumination compensation, eliminate the interference of ambient light on data, and improve the accuracy and consistency of data collected at different time periods. The DJI Terra software was used to plan the UAV route. The course and side overlap rates were 80%, and the image resolution was 1.6 cm/pixel. The lens parameters for the DJI Genie 4 Multispectral Edition are six 1/2.9-inch CMOS, including one colour sensor for visible light imaging and five monochrome sensors for multispectral imaging. RGB and single-band orthophoto images at different flight heights can be obtained by using Pix4D mapper software for image stitching. The multi-spectral orthophoto images of five bands are imported into ENVI software for band synthesis, and the pixel DN value is converted into reflectivity using a fast radiation correction tool.

Figure 3　UAV multispectral images acquisition system

2.2.2. Soil moisture content data acquisition

After the UAV image acquisition was completed, the soil moisture content of the soybean root domain was measured by soil drilling and drying method in the middle of two soybeans in each test area in time. According to the depth of the main root activity layer of soybean 0-20 cm, the soil sample was taken out and quickly loaded into the aluminum box for weighing. After drying at 105°C in the drying oven, the soil mass moisture content was weighed and calculated, and the soil volume moisture content was finally obtained according to the soil bulk density. Six replicates were taken in each plot to reduce the error, and the average soil moisture content was taken to represent the average soil moisture content in the sampling area.

2.2.3 Construction and selection of spectral index

According to the spectral absorption characteristics of vegetation, the dimensionless index parameter formed by linear or nonlinear combination of reflectance between different bands of remote sensing image is called vegetation spectral index. The index is a simple and effective empirical measure of surface vegetation status, and can reflect the difference between vegetation reflectance and soil background in the visible and near-infrared bands[16]. It has been pointed out in the literature that the leaf area index, aboveground biomass and yield of vegetation are closely related to the empirical vegetation indexes such as differential vegetation index (DVI), ratio vegetation index (RVI), normalized vegetation index (NDVI), enhanced vegetation index (EVI) and soil adjusted vegetation index (SAVI). Therefore, this study selected 15 vegetation spectral indices to construct a model, and the specific calculation formula is shown in Table 1.

Table 1　Empirical vegetation spectral indexes and calculation formulas

Vegetation Index	Calculation formula	Reference
Difference vegetation index (DVI)	$R_{NIR}-R_{RED}$	[17]
Ratio Value Vegetation Index (RVI)	R_{NIR}/R_{RED}	[18]
Triangle Vegetation Index (TVI)	$0.5*[120*(R_{NIR}-R_G)]-200*(R_{RED}-R_G)$	[19]
Optimization Vegetation Index (VIopt)	$1.45*(R_{NIR}*R_{NIR}+1)/(R_{RED}+0.45)$	[20]
Grassland Chlorophyll content vegetation Index (GCI)	R_{NIR}/R_G-1	[21]
Chlorophyll Index of red edges (CIre)	$R_{NIR}/R_{RE}-1$	[22]
MERIS Terrestrial Chlorophyll Index (MTCI)	$(R_{NIR}-R_{RE})/(R_{RE}-R_{RED})$	[20]
Normalized Difference Red edge index (NDRE)	$(R_{NIR}-R_{RE})/(R_{NIR}+R_{RE})$	[20]
Modified Triangle Vegetation Index (MTVI)	$1.2*(1.2(R_{NIR}-R_G)-2.5(R_{RED}-R_G))$	[20]
Normalized Difference Vegetation Index (NDVI)	$(R_{NIR}-R_{RED})/(R_{NIR}+R_{RED})$	[23]
Enhanced Vegetation Index (EVI)	$2.5*(R_{NIR}-R_{RED})/(R_{NIR}+6.0R_{RED}-7.5R_B+1)$	[24]
Soil Adjustment Vegetation Index (SAVI)	$(1+0.5)*(R_{NIR}-R_{RED})/(R_{NIR}+R_{RED}+0.5)$	[25]
Optimized Soil Adjusted Vegetation Index (OSAVI)	$(1+0.16)*(R_{NIR}-R_G)/(R_{NIR}+R_G+0.16)$	[26]
Green Normalized Difference Vegetation Index (GNDVI)	$(R_{NIR}-R_G)/(R_{NIR}+R_G)$	[27]

2.2.4 Division of sample set, model method and model evaluation

In this study, 162 groups of soil moisture content samples and spectral data samples were obtained based on field experiments. The 162 groups of soil moisture content samples were sorted from small to large, and 2/3 samples were randomly selected as the modeling set, and the remaining 1/3 samples were used as the verification set. Table 2 below shows the statistical characteristics of the sample size and yield of the modeling set and the validation set. Based on the calculated 15 spectral indices, the correlation between each spectral index and soil water content was analyzed, and the 10 vegetation indices with the highest correlation coefficient (R) were selected as the input variables of the model. SVM, RF and BPNN models were used to predict soybean LAI and aboveground biomass. Subsequently, support vector machine (SVM), random forest (RF) and back propagation neural network (BPNN) were used to model soil moisture content, respectively. The detailed introduction of the above machine learning models please referred to Tang et al. (2022)[28] and Tang et al. (2023)[29]. The Sigmoid is used to construct the function ELM model, and the hidden layer parameter $(a_i, b_i)^L_{i=1}$ is randomly generated in the range of [–1, 1], and the number of hidden layer nodes is set to 1000[30]; the number of neurons was gradually increased to 120 with 10 as the initial value and 10 as the step length. Each model was run 100 times to select the optimal training results. Finally, the number of neurons was 50. In the construction of the RF model, after parameter optimization and multiple training, the number of decision trees in the soil moisture model is set to 500[31]. The hidden layer transfer function in BPNN is set to TANSIG, and the Levenbeger-Marquardt (Train-LM) algorithm based on numerical optimization theory is used as the network training function. After many trainings, the number of neurons in the middle layer is determined to be 15[18].

The root mean square error (*RMSE*), coefficient of determination (R^2) and mean relative error (*MRE*) were used to evaluate the model fitting results. The prediction accuracy of the model was positively correlated with the coefficient of determination (R^2). The smaller *RMSE* and *MRE* indicate that the performance of the model is more stable and the prediction results are more concentrated. The calculation formula is as follows[29]:

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

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

$$MRE = \frac{1}{n}\sum_{i=1}^{n}\frac{|\hat{y}_i - y_i|}{y_i} \times 100\% \tag{3}$$

Table 2 Statistics of SMC in soybean.

Indexes	Modelling set	Validation set
Sample size	108	54
Maximum values (%)	22.114	22.785
Minimum values (%)	12.525	12.684
Mean (%)	18.111	18.203
Standard deviation (%)	2.425	2.402
Coefficient of variation (%)	13.391	13.198

3 Results

3.1 Correlation analysis between vegetation index and soil moisture content

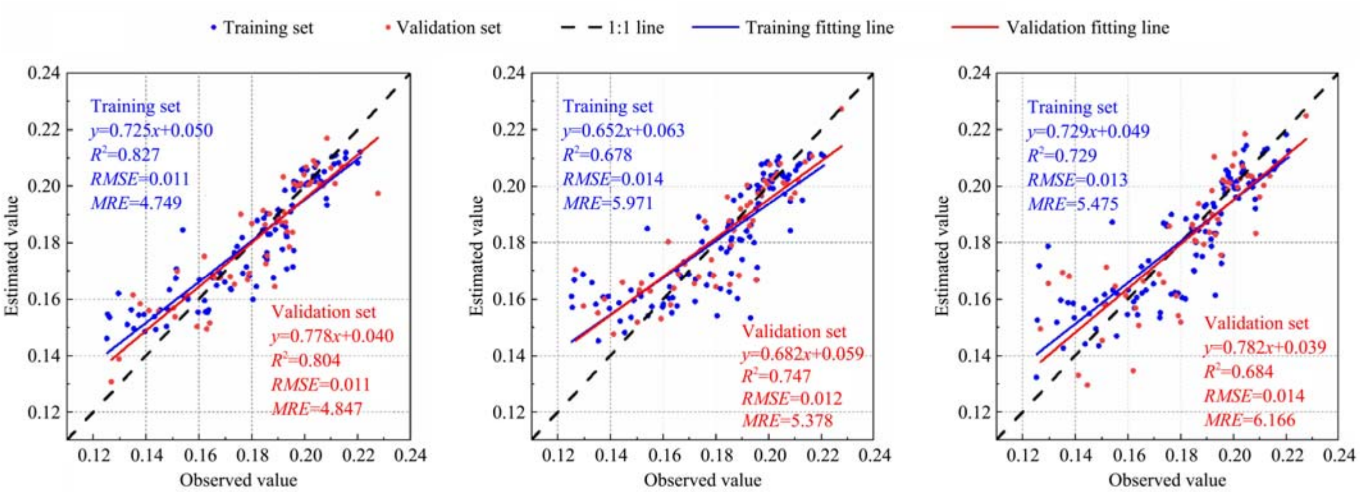
The correlation between soil moisture content measured in the data set and 15 vegetation indexes was analyzed, and the calculation results are shown in Table 3. The correlation coefficient of GOSAVI was the highest (0.740). Ten vegetation indexes were selected from large to small as the input of soil moisture monitoring model, which were GOSAVI, OSAVI, SAVI, EVI, DVI, MTCI, TVI, Cire, VIopt. The direct correlation coefficient between each index selected as model input and soil moisture content is higher than 0.63, indicating that each index is more sensitive to the change of soil moisture content.

Table 3 Calculation of correlation coefficients between vegetation index and soil moisture content

Vegetation Index	DVI	RVI	TVI	VIopt	GCI	CIRE	MTCI	NDRE	MTVI	NDVI	EVI	GOSAVI	SAVI	OSAVI	GNDVI
Soil water content	0.659	0.551	0.643	0.632	0.623	0.634	0.648	0.621	0.651	0.451	0.725	0.740	0.732	0.732	0.577

3.2 Construction of soybean root zone soil moisture content estimation model

Taking the vegetation index combination selected by 3.1 as the independent variable and the soil moisture content as the response variable, the LAI estimation model of soybean during the whole growth period was constructed by RF, ELM and BPNN respectively. The accuracy of the model was comprehensively evaluated from three aspects of R^2, *RMSE* and *MRE*. The prediction results of different modeling methods for soybean leaf area are shown in Figure 4 and Table 4.



a. The fitting results of RF model b. The fitting results of ELM model c. The fitting results of BPNN model

Figure 4 Prediction results of modelling set and validation set of wheat SMC inversion model with different input variables and modelling methods

Table 4 Comparison of precision test results of estimation models.

Model	set R^2		set *RMSE*		set *MRE*	
	Modelling	Validation	Modelling	Validation	Modelling	Validation
RF	0.817	0.804	0.011	0.011	4.749	4.847
ELM	0.678	0.747	0.014	0.012	5.971	5.378
BPNN	0.729	0.684	0.013	0.014	5.475	6.166

The results showed that the R^2 of the modeling set and the validation set of the soybean soil moisture monitoring model based on RF were 0.816 and 0.803, *RMSE* were 0.011, and *MRE* were 4.749 and 4.847, respectively. The R^2 of the modeling set and the validation set of the soybean soil moisture monitoring model based on ELM were 0.729 and 0.684, the *RMSE* were 0.013 and 0.014, and the MRE were 5.475 and 6.166, respectively. The R^2 of the modeling set and validation set of the soybean soil moisture monitoring model based on BPNN were 0.678 and 0.747, *RMSE* were 0.014 and 0.012, and *MRE* were 5.970 and 5.238, respectively. It is not difficult to find that the soybean soil moisture content monitoring model based on RF can achieve the highest prediction accuracy under the same input variables.

4 Discussion

Soil moisture content is one of the important indicators of soil moisture. Although predecessors have achieved good research results in the inversion of soil moisture content, there are certain deficiencies. The study of bare soil moisture content[5,19] is difficult to meet the needs of actual farmland production. The sampling of the ground object spectrometer[20] is time-consuming and laborious, and it is difficult to monitor the soil moisture content information at the regional scale. Tian et al. (2020)[1] and Wang et al. (2018)[21] constructed the soil moisture content inversion model based on the spectral data of winter wheat returning green period, but this study failed to obtain the UAV image data of the whole growth period. Zhang et al. (2019)[32] established an inversion model based on the average soil moisture content of maize root domain, and did not explore the soil moisture content data under multiple growth periods.

Unmanned Aerial Vehicle (UAV) mounted multispectral technology for monitoring soil water content has the following advantages over other methods (Wang et al., 2018; Seo et al., 2021; Zhang et al., 2023): (1) Efficient: UAVs are able to cover large areas of land quickly and collect the required data, which significantly improves the speed and efficiency of data collection. (2) High resolution: The multi-spectral sensor carried by the UAV can acquire high-resolution image data, which means that finer analyses can be performed and changes in soil water content can be detected on a small scale. (3) Reduced manual interference: Traditional sampling methods usually need to be carried out in the field, which may cause a certain degree of disturbance to the land. In contrast, drone remote sensing techniques do not require direct contact with the soil and can be monitored without disturbing the land. (4) Timeliness: UAVs can be flown as often as needed, offering the possibility of real-time monitoring, allowing soil moisture content to be monitored dynamically at critical times (e.g., before and after planting or after irrigation). (5) Cost-effectiveness: As the cost of drones and multispectral sensors is decreasing with technological advances, their cost-effectiveness is gradually increasing, especially when compared to previous methods that were extensively labour- and material-resource-intensive. (6) Ease of access: For areas with complex terrain or difficult access (e.g., mountainous areas, wetlands, etc.), drones are an ideal tool for obtaining relevant data. (7) Data diversity: Multi-spectral technology can acquire data in multiple bands at the same time, which can be used not only for monitoring soil water content, but also for other analyses, such as assessing the health of vegetation and identifying soil types.

In our study, through the correlation analysis of vegetation index and soil moisture content, it is found that several vegetation indexes related to vegetation index SAVI have good correlation with soil moisture content. Vegetation index SAVI is a vegetation index that can properly describe the ‘simple model’ of soil-vegetation system. Its core principle is NIR-red space, which is sensitive to the change of soil moisture content[22]. Therefore, it is not difficult to obtain the results of high correlation between this series of indexes and soil moisture content, that is, the change of SAVI can monitor crop soil moisture content in real time, which is similar to the research results of Deng et al. (2023)[23].

In addition, field soybeans under different field treatments were used as research objects to accurately extract vegetation canopy spectral information, and machine learning methods were used to construct models. After comparative analysis, it was found that among the three modeling methods selected in this study, the soybean soil moisture content monitoring model based on RF had the highest accuracy, indicating that RF had more advantages than other models in inverting soybean soil moisture content, which was basically consistent with the results of previous crop physiological growth indicators. Previous studies have shown that the prediction accuracy of the estimation model is greatly affected by different modeling methods[24]. The results of this study show that the prediction accuracy of ELM is lower than that of RF model. In the face of high-dimensional data, ELM will make noise variables unable to be eliminated through effective data preprocessing steps[30]. The BPNN model estimation accuracy is low, which may be due to the low generalization ability caused by relatively few samples[18]. RF is a machine learning method with comprehensive thinking, it has strong self-learning ability, strong tolerance to noise and outliers, and is not easy to over-fit[25,26]. Therefore, RF can be used as the preferred method for monitoring and modeling of soybean soil water content. This study can better provide real-time and efficient technical services for crop soil water stress monitoring in practical applications.

At present, there are still some problems to be solved in the study of crop growth estimation model and yield estimation based on empirical vegetation index. For example, the correlation coefficient changes and model inversion accuracy of different vegetation indexes in different regions, different crops in the same region, or even the same crop in the same region but in different periods may be different[27]. In addition, in the later stage of this study, we can also try to use a hyperspectral spectrometer with more bands to collect spectral information, so as to avoid the adverse effects of multi-spectral information loss.

5 Conclusions

In our study, the spectral reflectance of each band was extracted by obtaining the multi-spectral information of soybean at three different growth stages, and the vegetation index was calculated. At the same time, the soil moisture content of soybean was measured and analyzed. Combined with the measured data, RF, ELM and BPNN were used to estimate the soil moisture content of soybean. The results show that:

(1) The spectral index OSAVI has the highest correlation with soybean soil moisture content, which is 0.740. The change of OSAVI can monitor the change of soybean soil moisture content in real time.

(2) The accuracy of RF and soybean soil moisture content monitoring models was higher than that of ELM and BPNN models. The R^2 of the modeling set and the validation set was above 0.8, RMSE was lower than 0.015, and MRE was lower than 5.0.

Author Contributions

Data curation: Zijun Tang; Investigation: Zijun Tang; Methodology: Zijun Tang, Wei Zhang and Xin Wang; Project administration: Youzhen Xiang; Resources: Youzhen Xiang and Junying Chen; Software: Youzhen Xiang; Supervision: Youzhen Xiang; Visualization: Zijun Tang; Writing – original draft: Zijun Tang; Writing – review & editing: Zijun Tang and Youzhen Xiang.

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Data Availability Statement:

Not applicable

Conflicts of Interest:

The authors declare no conflict of interest.

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