



Article

Detection of Peanut Leaf Spot Disease Based on Leaf-, Plant-, and Field-Scale Hyperspectral Reflectance

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Abstract: Leaf spot (LS) caused by *Cercosporidium personatum* is one of the most harmful peanut diseases in the late growth stage and severely affects the yield of peanuts. Hyperspectral disease detection technology is efficient, objective, and accurate and is suitable for large-scale crop management practices. To establish a multi-scale spectral index (SI) with high accuracy and stability for the detection of peanut LS disease, the spectral reflectance of different disease severity levels at leaf, plant, and field scales was collected, and the difference in wavelength caused by disease severity was analyzed using the mean, variance, and dispersion matrix of hyperspectral reflectance. Meanwhile, the feature weights at different scales were obtained using Relief-F, and the average feature weights identified 540, 660, and 770 nm as multi-scale sensitive wavelengths. Three new SIs were constructed by combining single, ratiometric, and normalized wavelengths. The new SIs were compared and analyzed with 35 commonly used SIs by correlation analysis and M-statistic values, and 6 SIs were significantly correlated with disease severity levels and had good separability. Finally, k-nearest neighbor (KNN) and multinomial logistic regression (MLR) were used to evaluate the ability of the above SIs to detect LS severity. The results showed that the leaf spot multi-scale spectral index (LS-MSSI) constructed in this study was superior to the other SIs and obtained high accuracy at different scales simultaneously. At the leaf and plant scales, the MLR obtained high accuracy, with the overall accuracy (OA) reaching 93.77% and 92.50% and Kappa reaching 91.59% and 89.97%, respectively. At the field scale, the KNN obtained high accuracy, with the OA and Kappa reaching 90.29% and 87.04%, respectively. The LS-MSSI proposed in this study has high accuracy, stability, and robustness in the detection of LS severity at multiple scales, providing a technical basis and scientific guidance for the detection and precise management of peanuts.

Keywords: peanut; leaf spot; hyperspectral reflectance; multiple scale; spectral index

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1. Introduction

The peanut (*Arachis hypogaea* L.) is an important economic crop and a major source of protein and vegetable oil. Peanuts are widely grown in more than 100 countries worldwide, especially in China, India, Nigeria, and the United States [1]. Climate and environmental changes have continuously expanded the distribution, host range, and influence of peanut diseases, threatening food security and the environment [2,3]. Among them, leaf spot (LS) caused by *Cercosporidium personatum* is a common peanut disease in the late growth stage. Crops infected with LS show dark brown or black lesions on the leaves. If left uncontrolled, defoliation rates can reach 100% and yield losses of up to 70% [4]. At present, fungicide spraying is a standard measure to control LS. However, the excessive use of fungicides increases the cost of peanut disease management and causes problems such as environmental pollution and threats to food safety [5]. Therefore, precision spraying

according to the occurrence of diseases in the field can effectively save economic costs, protect the environment, and ensure food safety [6].

The traditional way to obtain crop disease information in the field is visual investigation. This method requires the relevant expertise of plant protection personnel and has the disadvantages of being highly subjective, inefficient, and lagging. In addition, an enzyme-linked immunosorbent assay (ELISA) and polymerase chain reaction (PCR) based on biochemical technology can accurately detect disease severity. However, the processing of these methods is complex, has high loop-breaking, and is time-consuming [7,8]. Neither of these methods can quickly and accurately obtain information on the severity and spatial distribution of crop diseases, so it is difficult to meet the needs of large-scale scientific monitoring and early detection of crop diseases.

Remote sensing technology is a non-contact, long-distance detection technology that can use electromagnetic radiation or reflection characteristics of objects to detect and identify diseases. It has been one of the most important tools for agricultural monitoring in recent years due to its advantages of being objective, non-destructive, and efficient [9]. Among the different types of remote sensing technology, hyperspectral technology has been widely studied in crop identification [10], biomass estimation [11], pest detection [12], and other aspects. However, since hyperspectral data contain redundant information, many scholars reduce the dimension of data by selecting sensitive wavelengths and constructing a spectral index (SI) to reduce application costs and improve the speed and accuracy of the disease detection model. The authors of [13] collected the hyperspectral reflectance of wheat powdery mildew at the leaf scale, selected sensitive wavelengths using sub-window permutation analysis (SPA), and constructed SI. The authors of [14] collected the leaf-scale hyperspectral reflectance of the late blight, target, and bacterial spot disease of tomatoes at different stages and selected 30 SIs by principal component analysis (PCA). The authors of [15] collected the hyperspectral reflectance of healthy and diseased wheat ears at flowering and filling stages in the laboratory. The sensitive wavelengths were selected using random forest (RF), and a new *Fusarium* disease index (FDI) was constructed. The above studies used the leaf-scale hyperspectral reflectance collected in the laboratory to establish SIs to detect crop diseases. Leaf-scale hyperspectral reflectance is less susceptible to environmental factors such as light, temperature, and humidity. It can accurately detect the subtle changes in crops affected by diseases, which is suitable for basic research under laboratory conditions. However, the low throughput of the leaf-scale technique makes it unsuitable for practical applications [16].

The hyperspectral reflectance acquired on the ground in the field maintains a high spatial resolution and improves the throughput of measurement to a certain extent. The authors of [17] analyzed the plant-scale hyperspectral reflectance of healthy and infected yellow rust wheat at different stages. The obtained sensitive wavelengths were linearly combined to select the optimal SI of yellow rust at different growth stages of wheat. The authors of [18] used Relief-F and correlation analysis on the plant-scale hyperspectral reflectance of winter wheat powdery mildew to identify the most sensitive wavelengths and generated a new vegetation index based on the normalized difference vegetation index (NDVI) approach. The authors of [19] collected the hyperspectral reflectance of tea anthracnose and used spectral sensitivity to select sensitive wavelengths. The tea anthracnose ratio index (TARI) and tea anthracnose normalization index (TANI) were created using sensitive wavelengths. Due to the short distance from the target crop, the plant-scale hyperspectral reflectance collected in the field could obtain high accuracy and be less affected by the interference of the environment. However, its limited area for detecting crops is not conducive to the large-scale detection of crop diseases.

Compared with leaf-scale and plant-scale techniques, unmanned aerial vehicle (UAV) remote sensing technology is efficient, flexible, and convenient and can be applied to field-scale disease detection. The authors of [20] collected the hyperspectral reflectance of the target spot and bacterial spot of tomato at different stages at leaf and field scales and selected the optimal SI from 35 SIs. The authors of [21] used the leaf-scale and field-scale

hyperspectral reflectance to detect powdery mildew with different pumpkin disease levels. The selected sensitive wavelengths and SIs were evaluated at different scales, and the best SIs at different scales for different periods were obtained. The authors of [22] collected leaf-scale hyperspectral reflectance in the laboratory to classify citrus canker disease at different stages using radial basis function (RBF) and k-nearest neighbor (KNN) and validated them at the field scale. The authors of [23] obtained the hyperspectral reflectance of tomato yellow leaf curl, bacterial spot, and target spot at leaf and field scales, respectively. The infected and healthy plants were classified by stepwise discriminant analysis (STDA) and RBF. The hyperspectral reflectance acquired by UAVs is susceptible to factors such as light intensity, incident light angle, and environmental conditions, making the stability of field-scale disease detection models poor.

The studies mentioned above mostly used leaf-scale hyperspectral reflectance to obtain optimal SIs and applied them at the field scale. However, the hyperspectral reflectance at different scales responds to different disease features. For example, leaf-scale hyperspectral reflectance mainly responds to the effect of disease on the biochemical indicators of leaves. However, plant-scale and field-scale hyperspectral reflectance can also respond to the effect of disease on plant canopy structure. Therefore, there are some biases in the transferability and reliability of SIs between different scales, which leads to the ineffective results of leaf-scale SIs in applications to field-scale disease detection [24–26]. Therefore, to explore the transferability and reliability of SIs in spans-scale disease detection more comprehensively, the main work of this study is as follows: (1) The hyperspectral reflectance of peanut LS disease at leaf, plant, and field scales was obtained, and the association and difference in spectral response caused by the disease between different scales were explored by data analysis. (2) The sensitive wavelength selection algorithm was used to find the feature weights of each wavelength at different scales, and the multi-scale feature weights were determined by combining the feature weights of different scales. (3) The multi-scale SIs were constructed using the commonly used waveband combination method. (4) The ability of the constructed SIs to detect the LS disease severity was evaluated using different classifiers.

2. Materials and Methods

2.1. Overview of the Experiment Site

The experimental site was located at the Haicheng campus of Shenyang Agricultural University, Gengzhuang Town, Anshan City, Liaoning Province, China (N40°58′41.64″–N40°58′43.05″, E122°43′29.29″–E122°43′30.14″, 13 m above sea level), as shown in Figure 1. The peanuts tested were of the LS-susceptible variety ‘Baisha’, the main cultivar in Liaoning. Peanuts were planted on 20 May 2021, with a row spacing of 45 cm and a plant spacing of 35 cm, and the test field area was about 1200 m². N-P₂O₅-K₂O compound fertilizer of 81 kg ha^{−1} was applied before sowing. Weeds, pests, and other diseases were controlled according to local agronomic measures. LS occurred naturally throughout the experimental field. Sixty days after emergence, some of the crops in the field were infected with slight disease severity. In mid-August, the crops in the field were infected with different disease severity levels. Therefore, experiments were carried out on 15 August, 19 August, and 23 August.

2.2. Data Collection

2.2.1. Disease Severity Assessment

On the leaf scale, disease severity is mainly based on the percentage of the total area of disease symptoms on the leaves [27,28]. According to the Technical Regulations for Identification of Peanut Varieties Resistant to Leaf Spot Disease (DB21/T 3074–2018), LS was classified into six severity levels. Since detecting disease severity at mid-growth is a critical period for effective control of disease development, the experiment was conducted at the mid-growth stage. However, the disease at mid-growth did not develop to an extremely severe level, and level 5 and level 6 diseases were not detected at mid-growth. Therefore, LS leaves with four different severity levels, asymptomatic, initially symptomatic, moderately

symptomatic, and severely symptomatic, were collected according to the actual disease occurrence in the field, as shown in Table 1. In addition, since peanut leaf spot disease occurs naturally throughout the test field, detecting infected but asymptomatic samples in the field is very difficult. Therefore, this study defined all samples without disease spots on the leaves as the asymptomatic level (no distinction between healthy and infected but asymptomatic).

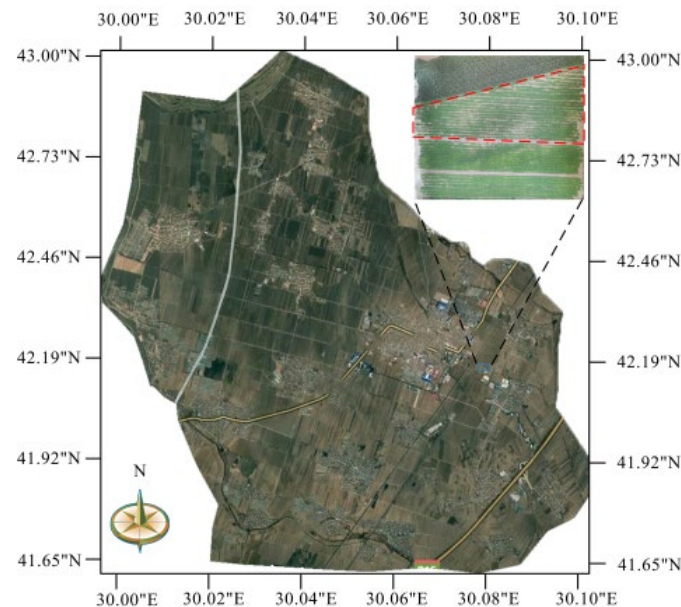


Figure 1. Location and overview of the experimental site.

Table 1. Disease severity levels at the leaf scale.

Level	Disease Severity	Area Ratio
A	Asymptomatic	DI = 0
I	Initially symptomatic	$0 < DI \leq 0.1$
M	Moderately symptomatic	$0.1 < DI \leq 0.25$
S	Severely symptomatic	$0.25 < DI \leq 0.5$

At the plant and field scales, disease severity is determined by the disease index (DI) [29]. DI is calculated as follows.

$$DI = \frac{0 \times n_0 + 1 \times n_1 + 2 \times n_2 + 3 \times n_3}{3 \times (n_0 + n_1 + n_2)} \quad (1)$$

where n_0 is the number of asymptomatic leaves, n_1 is the number of initially symptomatic leaves, n_2 is the number of moderately symptomatic leaves, and n_3 is the number of severely symptomatic leaves. Therefore, disease severity levels are defined at the plant and field scales. A: asymptomatic (DI = 0), I: initially symptomatic ($0 < DI \leq 0.1$), M: moderately symptomatic ($0.1 < DI \leq 0.25$), S: severely symptomatic ($0.25 < DI \leq 0.5$).

2.2.2. Leaf-Scale Spectral Collection

The HR2000+ high-resolution spectrometer from Azumi Optical Instruments (Shanghai) Co., Ltd., was used to equip a reflection sensor, and an HL-2000 tungsten halogen lamp light source was used to obtain the hyperspectral reflectance of leaves with different disease severity levels. Six fiber legs in the reflection probe are connected to the light source, and the other fiber leg is connected to the spectrometer to achieve optimal performance. The receiving angle of the probe is 24.8° . Before measurement, the holder held the probe at a

distance of 3 cm above the leaf, and the reflectance collected was the average reflectance of a circular area with a diameter of 1.3 cm. Before each measurement, the spectrometer was calibrated with a diffuse reflection reference plate. During the measurement, the reflectance of the area was measured 10 times, and the average was the absolute hyperspectral reflectance of the area. The range of the hyperspectral wavelengths was 190–1100 nm, and the spectral resolution was 1 nm (full width at half maximum, FWHM). Because of the noise between 190 and 400 nm and between 1000 and 1100 nm, the hyperspectral reflectance between 400 and 1000 nm was considered in this study. Figure 2 shows the leaves with different disease severity levels.

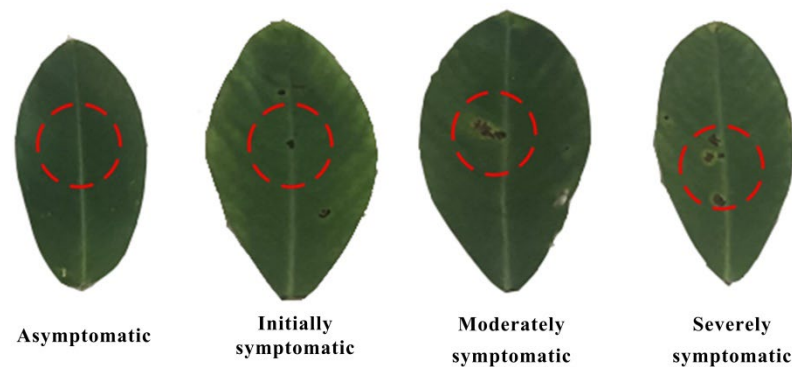


Figure 2. Leaves with different disease severity levels.

2.2.3. Plant-Scale Spectral Collection

The FieldSpec HandHeld 2 was used to obtain hyperspectral reflectance of the crop with different disease severity levels at the plant scale. The device has an effective wavelength range of 325–1075 nm, a spectral resolution of 3 nm (FWHM), and a field of view of 25°. Due to noise effects at both ends of the spectral range, the hyperspectral reflectance between 400 and 1000 nm was considered in this study. Measurements were conducted from 10:00 to 14:00 (Beijing time) on sunny days. Data were collected with the spectrometer probe at a distance of 0.5 m from the crop canopy, and the regions of interest (ROIs) collected were approximately 0.17 m². Panel radiation measurements were used to optimize and calibrate the instrument before each measurement. Ten repeated measurements were performed over the same region, and their average was calculated as the absolute hyperspectral reflectance of the ROI. Figure 3 shows the canopy images with different disease severity levels at the plant scale.

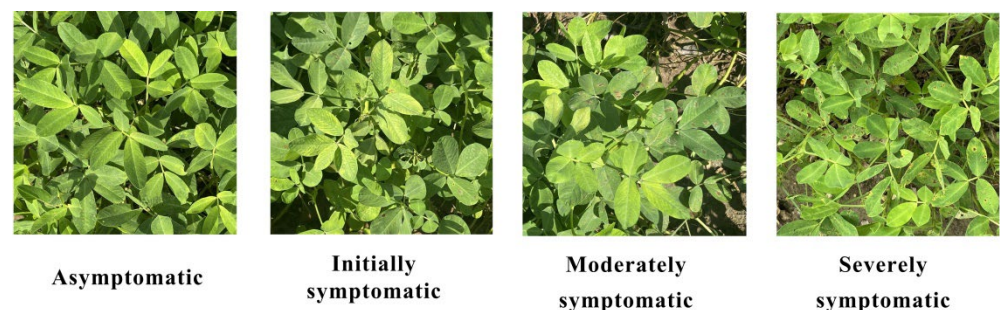


Figure 3. Canopy images with different disease severity levels at the plant scale.

2.2.4. Field-Scale Spectral Collection

The UAV Matrice 600 was selected as the remote sensing platform to obtain the field-scale hyperspectral reflectance. The remote sensing platform was equipped with GaiaSky-mini hyperspectral imager with a spectral range of 400–1000 nm and a resolution of 3.5 nm (FWHM). The UAV was flown at an altitude of 100 m and hovered to acquire data.

The acquired hyperspectral images were pre-processed with SpectralView software for lens calibration, reflectivity calibration, and atmospheric calibration. Hyperspectral reflectance was extracted from the pre-processed hyperspectral images using ENVI 5.3 software. ROIs were generated on the marked disease-level plants. The average of all pixels in the ROI was considered the absolute hyperspectral reflectance. Figure 4 shows the hyperspectral image at the field scale and a selected ROI. The leaf-scale and plant-scale spectral reflectance used in this study were automatically adjusted to a sampling interval of 1 nm on the device. At the field scale, the effect of the environment was reduced by increasing the sampling interval when collecting hyperspectral data. The sampling interval was adjusted to 1 nm during the pre-processing process. However, the errors caused by interpolation at the field scale are acceptable, and their effects are much smaller than those caused by the environment. In this study, the hyperspectral reflectance at different scales was uniformly adjusted to a sampling interval of 1 nm, allowing for a more accurate exploration of correlations and differences between wavelengths at different scales and more extensive validation and practical validation applications.

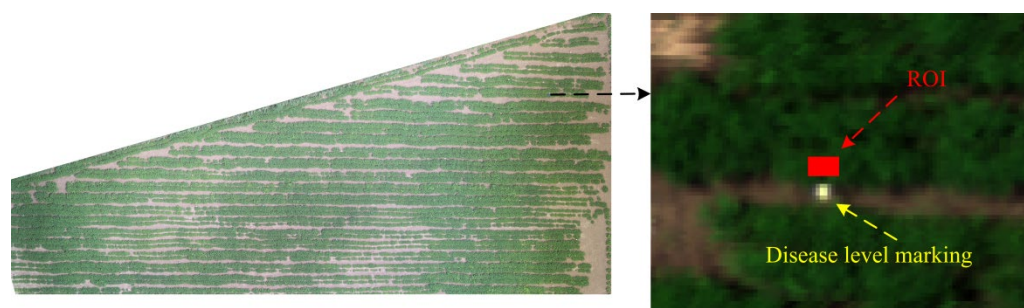


Figure 4. The hyperspectral image at the field scale and a selected ROI.

In this study, by excluding the hyperspectral data under the influence of noise, a total of 1071 spectral reflectances with different disease severity levels were collected at the leaf scale, 534 spectral reflectances with different disease severity levels were collected at the plant scale, and a total of 586 ROIs with different disease severity levels were selected from the hyperspectral images. The number of samples with different disease severity levels at the three scales is shown in Table 2.

Table 2. Number of samples at different scales.

Disease Severity	Leaf-Scale Samples	Plant-Scale Samples	Field-Scale Samples
Asymptomatic	261	136	148
Initially symptomatic	338	148	157
Moderately symptomatic	242	138	138
Severely symptomatic	230	112	143
Total	1071	534	586

2.3. Sensitive Wavelength Selection

Relief is a feature selection algorithm that can determine the feature weights of wavelengths [30]. Relief is widely used because of its simplicity, high operational efficiency, and satisfactory results, but it can only handle two data classes. The authors of [31] extended it and created Relief-F, which can handle multi-class problems. In this study, Relief-F was used to obtain the feature weights of wavelengths at different scales. Due to the high correlation between adjacent wavelengths of the hyperspectral reflectance, the wavelengths corresponding to the peaks of the feature weights in the local range were identified as sensitive wavelengths in this study.

2.4. SI Construction

In the field, the simple use of high spectral reflectance is not conducive to accurate and repeatable disease detection because solar irradiance varies with time and weather. Therefore, many scholars used a combination of wavelengths to avoid the negative effects of being susceptible to interference from environmental factors. This approach is called SI. In this study, the selected sensitive wavelengths were used to construct the SIs in the form of Table 3.

Table 3. Commonly used SI construction methods.

Method	Calculation Formula	Reference
Ratio spectral index (RSI)	$a \times \frac{R_{\lambda 1}}{R_{\lambda 3}} + b \times \frac{R_{\lambda 1}}{R_{\lambda 2}}$	[32]
Normalized difference spectral index (NDSI)	$a \times \frac{R_{\lambda 1} - R_{\lambda 3}}{R_{\lambda 1} + R_{\lambda 3}} + b \times \frac{R_{\lambda 1} - R_{\lambda 2}}{R_{\lambda 1} + R_{\lambda 2}}$	[32]
New spectral index (NSI)	$a \times R_{\lambda 1} + b \times \frac{R_{\lambda 2}}{R_{\lambda 3}}$	[33]

Note: λ_1 is the most sensitive wavelength, λ_2 and λ_3 are the second most sensitive wavelengths, and the coefficients a and b are determined by fitting Fisher discriminant analysis based on the training dataset.

Plant diseases can cause changes in chlorophyll content, water stress, and cell structure, and the changes caused by diseases can be evaluated by visible and near-infrared (NIR) bands [34,35]. Therefore, 35 commonly used and 3 new SIs were selected to detect the LS severity, as shown in Table 4.

Table 4. SIs used in this study.

NO.	SI	Calculation Formula	Reference
1	Simple ratio (SR)	$\frac{R_{695}}{R_{420}}$	[36]
2	Normalized difference vegetation index (NDVI)	$\frac{R_{800} - R_{670}}{R_{800} + R_{670}}$	[37]
3	Aphid index (AI)	$\frac{R_{761} - R_{908}}{R_{712} - R_{719}}$	[38]
4	Structural independent pigment index (SIPI)	$\frac{R_{800} - R_{445}}{R_{800} - R_{445}}$	[39]
5	Damage-sensitive spectral index-1 (DSSI-1)	$\frac{R_{719} - R_{873} - R_{509} - R_{537}}{R_{719} - R_{873} - R_{509} - R_{537}}$	[40]
6	Damage-sensitive spectral index-2 (DSSI-2)	$\frac{R_{747} - R_{901} - R_{537} - R_{572}}{R_{747} - R_{901} - R_{537} - R_{572}}$	[40]
7	Chlorophyll index (CI)	$\frac{R_{415} - R_{435}}{R_{415} + R_{435}}$	[41]
8	Chl stress index-1 (Chl SI-1)	$\frac{R_{415}}{R_{695}}$	[42]
9	Chl stress index-2 (Chl SI-2)	$\frac{R_{708}}{R_{715}}$	[43]
10	Chl stress index-3 (Chl SI-3)	$\frac{R_{915}}{R_{515}}$	[43]
11	Ratio analysis of reflectance spectral chlorophyll a (RARSa)	$\frac{R_{675}}{R_{700}}$	[44]
12	Ratio analysis of reflectance spectral chlorophyll b (RARSb)	$\frac{R_{675}}{R_{700} \times R_{650}}$	[44]
13	Ratio analysis of reflectance spectra chlorophyll c (RARSc)	$\frac{R_{760}}{R_{500}}$	[44]
14	Leaf hopper index (LHI)	$\frac{R_{761} - R_{691}}{R_{550} - R_{715}}$	[45]
15	Nitrogen stress index-1 (NSI-1)	$\frac{R_{415}}{R_{710}}$	[42]
16	Nitrogen stress index-2 (NSI-2)	$\frac{R_{517}}{R_{413}}$	[43]
17	Plant pigment ratio (PPR)	$\frac{R_{550} - R_{450}}{R_{550} + R_{450}}$	[46]
18	Physiological reflectance index (PRI)	$\frac{R_{550} - R_{531}}{R_{550} + R_{531}}$	[47]
19	Transformed chlorophyll absorption and reflectance index (TCARI)	$3 \times [(R_{700} - R_{670}) - \frac{0.2 \times (R_{700} - R_{550}) \times R_{700}}{R_{670}}]$	[48]
20	Modified chlorophyll absorption in reflectance index-1 (MCARI-1)	$1.2 \times [2.5 \times (R_{800} - R_{670}) - 1.3 \times (R_{800} - R_{550})]$	[35]
21	Modified chlorophyll absorption in reflectance index-2 (MCARI-2)	$\frac{1.5 \times [2.5 \times (R_{800} - R_{670}) - 1.3 \times (R_{800} - R_{550})]}{SQ[(2 \times R_{800} + 1)^2 - (6 \times R_{800} - 5 \times SQ(R_{670})) - 0.5]}$	[35]
22	Modified triangular vegetation index-1 (MTVI-1)	$1.2 \times [1.2 \times (R_{800} - R_{550}) - 2.5(R_{670} - R_{550})]$	[35]

Table 4. Cont.

NO.	SI	Calculation Formula	Reference
23	Modified triangular vegetation index-2 (MTVI-2)	$\frac{1.5 \times [1.2 \times (R800 - R550) - 2.5(R670 - R550)]}{SQ[(2 \times R800 + 1)^2 - (6 \times R800 - 5 \times SQ(R670)) - 0.5]}$	[35]
24	Plant senescence reflectance index (PSRI)	$\frac{R678 - R550}{R750}$	[49]
25	Water index (WI)	$\frac{R970}{R900}$	[50]
26	Triangle vegetation index (TVI)	$0.5 \times [120 \times (R750 - R550) - 200 \times (R670 - R550)]$	[51]
27	Normalized water index-1 (NWI-1)	$\frac{R970 - R900}{R970 + R900}$	[52]
28	Normalized water index-2 (NWI-2)	$\frac{R970 - R850}{R970 + R850}$	[52]
29	Normalized pigment chlorophyll ratio index (NPCl)	$\frac{R680 - R430}{R680 + R430}$	[53]
30	Anthocyanin reflectance index (ARI)	$\frac{1}{R550} - \frac{1}{R700}$	[54]
31	Pigment-specific simple ratio (PSSRa)	$\frac{R680}{R800}$	[55]
32	Pigment-specific simple ratio (PSSRb)	$\frac{R635}{R800}$	[55]
33	Leaf spot index (LSI)	$\frac{R938 - R761}{R938 + R761}$	[56]
34	Early leaf spot index (ELSI)	$\frac{R600}{R938 + R761}$	[57]
35	Late leaf spot index (LLSI)	$\frac{R430}{R701}$	[57]
36	Leaf spot multi-scale spectral index 1 (LS-MSSI 1)	$\frac{R770}{R660} + \frac{R770}{R540}$	This study
37	Leaf spot multi-scale spectral index 2 (LS-MSSI 2)	$\frac{R770 - R660}{R770 + R660} + \frac{R770 - R540}{R770 + R540}$	This study
38	Leaf spot multi-scale spectral index 3 (LS-MSSI 3)	$\frac{R770}{R660} + \frac{R660}{R540}$	This study

2.5. Classification Methods

2.5.1. KNN

KNN applies to classification tasks in a supervised learning environment and is one of the most classical machine learning algorithms [58]. The main idea of KNN is to determine the category to which one belongs based on the category of neighbors that are close to each other. The algorithm first calculates the distance between the test samples and all samples in the training dataset. Secondly, the nearest K samples in the distance are found as the neighbors of the test sample. Finally, the category with the highest frequency among the K samples is the category to which the test sample belongs. KNN is efficient and easy to implement without estimating parameters and training.

2.5.2. Multinomial Logistic Regression

Multinomial logistic regression (MLR) is the extension for the (binary) logistic regression when the categorical dependent outcome has more than two levels [59]. The main idea of MLR is to use the activation function to predict the probability of the dependent variable (category) by the linear combination of independent variables (features) and corresponding parameters. Among them, the parameters corresponding to the independent variables are calculated by the training dataset, and these parameters become regression coefficients. In this study, the softmax function was used as the activation function, and the log-likelihood loss function was used as the loss function. The iterative weighted least square was used to find the optimal regression coefficient.

2.6. Flow of the Study

In this study, the hyperspectral reflectance of peanut LS disease with varying severity at the leaf, plant, and field scales was obtained. The multi-scale SIs for detecting the severity of peanut LS disease were determined by data analysis, feature weight calculation, sensitive band selection, and spectral index construction. The ability of the SIs to detect the severity of peanut LS disease was evaluated using KNN and MLR classifiers. The specific process is shown in Figure 5.

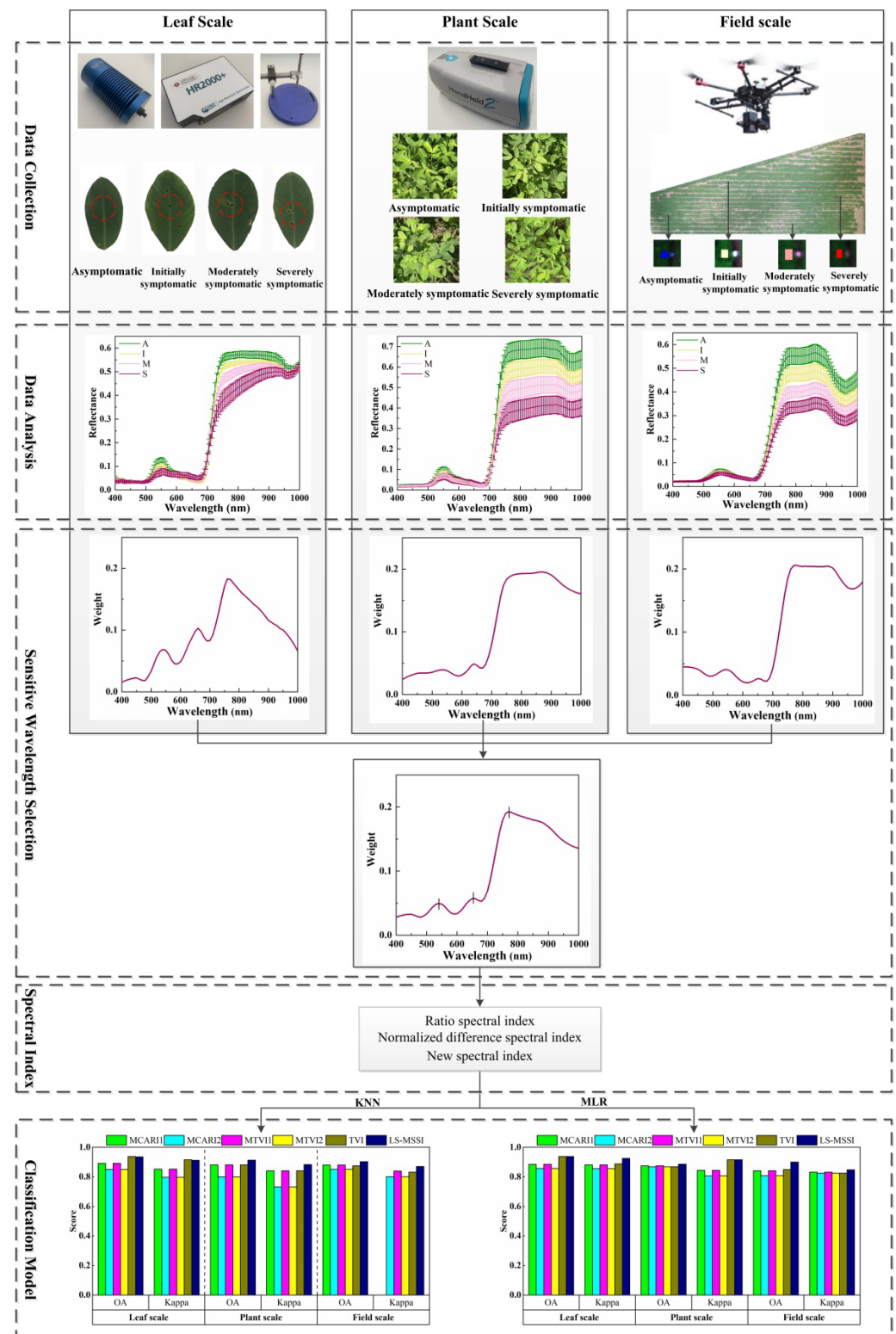


Figure 5. Flowchart of peanut LS detection using multi-scale hyperspectral reflectance.

3. Evaluation Indicators

3.1. Evaluation Indicators of Wavelength

Mean and variance were used to evaluate the difference in wavelengths qualitatively. The mean of the spectra assesses the overall features of the spectral reflectance with different disease severity levels. The variance assesses the consistency of spectral reflectance for

the same disease severity level and the difference in spectral reflectance between different disease severity levels.

The dispersion matrix was used to evaluate the separability of the wavelengths quantitatively. The dispersion matrix is a favorable indicator of separability evaluated in linear discriminant analysis (LDA). According to [60], the overall dispersion matrix is defined as follows:

$$S_T = \sum_{i=1}^C n_i (m_i - \mu)(m_i - \mu)^T + \sum_{i=1}^C \sum_{x \in C_i} (x - m_i)(x - m_i)^T \quad (2)$$

where C is the total number of classes, n_i is the number of samples in class i , m_i is the mean of class i , and μ is the mean of the overall sample.

3.2. Evaluation Indicators of SI

The M-statistic values were used to evaluate the separation of SI to distinguish between different disease levels [61]. The M-statistic value was normalized to the difference between the means of the two categories by the sum of their standard deviations. $M < 1.0$ means poor separation, $M > 1.0$ means good separation, and a larger M-statistic value means better separation [62]. The M-statistic value is defined as follows:

$$M = \frac{(\text{Mean}_\alpha - \text{Mean}_\beta)}{(\sigma_\alpha + \sigma_\beta)} \quad (3)$$

where α and β represent different categories.

Overall accuracy (OA) and Kappa coefficients were used to evaluate the ability of SI to detect disease severity. All of these indicators can be calculated based on true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN), as shown in Table 5. The specific formulas for OA and Kappa are as follows.

$$OA = \frac{TP + TN}{TP + TN + FP + FN} \quad (4)$$

$$P_e = \sum_{i=1}^C \frac{(TP_i + FN_i) + (TP_i + FP_i)}{N^2} \quad (5)$$

$$\text{Kappa} = \frac{OA - P_e}{1 - P_e} \quad (6)$$

where N is the total number of samples.

Table 5. Confusion matrix.

Actual Class	Predicted Class	
	Positive	Negative
Positive	TP	FN
Negative	FP	TN

4. Results

4.1. Multi-Scale Spectral Features

Figure 6 shows the mean and variance of spectral reflectance with different disease severity levels at multiple scales. The absorption of photosynthetic pigments was higher in the visible range, and the peak appeared at 520–570 nm (green band). At 650–760 nm (red band), it reached the trough. At 670–760 nm (red edge band), the reflectance gradually increased to a peak and remained at a high value at 760–900 nm (NIR band).

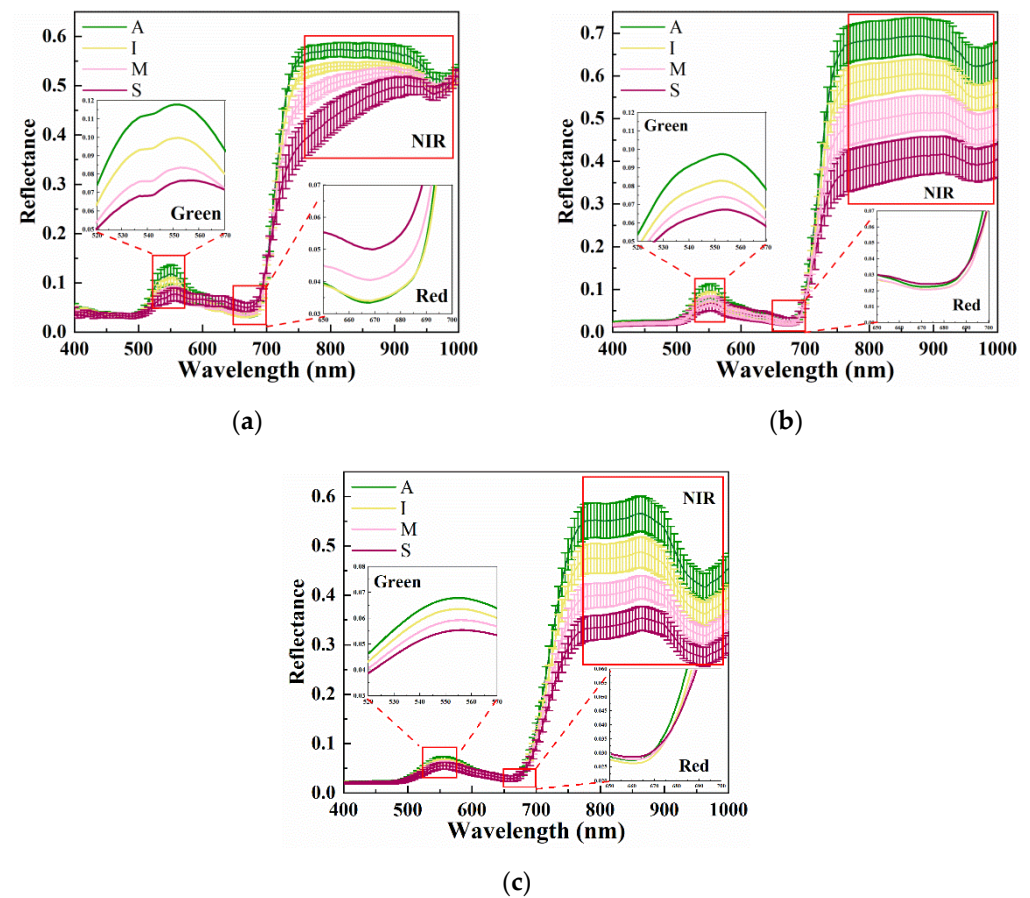


Figure 6. Mean and variance of the reflectance of different disease severity levels at multiple scales. (a) Leaf scale, (b) plant scale, and (c) field scale.

Figure 6a shows the leaf-scale spectral reflectance with different disease severity levels. At 520–570 nm, asymptomatic leaves had the highest reflectance. The reflectance decreased as the disease severity levels increased. At 650–670 nm, the reflectance of asymptomatic leaves was the smallest, and the reflectance increased slightly with the increase in disease severity levels; at 670–760 nm, the reflectance increased differently for each disease severity level, resulting in a blue shift of the ‘red edge’ of the reflectance. At 760–1000 nm, the highest reflectance was found in asymptomatic leaves, and the reflectance gradually decreased with the increase in disease severity levels. Meanwhile, the difference in the reflectance between different disease severity levels decreased with the increase in wavelength. Figure 6b shows the plant-scale spectral reflectance with different disease severity levels. At 520–570 nm, there were differences in reflectance between different disease severity levels. At 750–1000 nm, the difference in reflectance between different disease severity levels was larger. Figure 6c shows the field-scale spectral reflectance with different disease severity levels. A weak difference was shown in the green band between the different disease severity levels. At 750–1000 nm, there was a large variation in reflectance between different disease severity levels, similar to the plant scale.

4.2. Multi-Scale Spectral Separability

The separability of the wavelength was quantitatively evaluated by dispersion. Figure 7 shows the dispersion of all wavelengths at different scales. The dispersion was normalized to compare the relative importance of the separations, with ‘1’ representing the best separation and ‘0’ representing the worst separation. At the leaf scale, a large dispersion value appeared at 720–780 nm, where the maximum value was reached at 750 nm. At the same time, a local extreme value was observed at 546 nm, with a certain separability in the green band. At the

plant scale, a high separability was obtained at 730–950 nm, with the highest value at 760 nm. Meanwhile, a local extreme value was also obtained at 553 nm, but the relative dispersion value here was smaller than that at the leaf scale. At the field scale, a high separability was obtained at 750–900 nm, with the highest value at 780 nm. From the above results, it can be seen that the separability of the green band gradually decreased and that of the NIR band gradually increased as the spatial resolution decreased, which is consistent with the results of the qualitative evaluation analysis in Section 4.1.

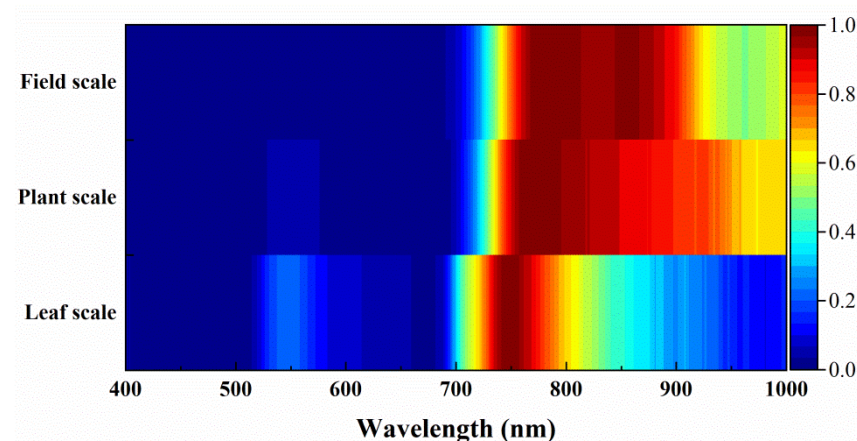


Figure 7. The dispersion of each wavelength at multiple scales.

4.3. Multi-Scale Sensitive Wavelength Selection

Relief-F was used to obtain the feature weights of wavelengths at multiple scales. The results are shown in Figure 8. At the leaf scale, higher weights were obtained in the NIR band. Among them, the highest weight was obtained at 760 nm. The weights gradually decreased as the wavelengths increased in the region of 760–1000 nm. Meanwhile, certain weights were obtained at 520–570 and 650–700 nm, and local peaks were obtained at 540 and 660 nm. At the plant scale, higher weights were obtained at 760–900 nm, and the highest weight was obtained at 770 nm. With increasing wavelengths, a smaller trend of weights was observed at 900–1000 nm. Local peaks were observed at 530 and 640 nm, but the weights decreased compared to the leaf scale. At the field scale, high and stable weights appeared at 760–900 nm, and the maximum weight was obtained at 770 nm. Local peaks appeared at 540 and 650 nm. The weights at different scales were considered together, and the weights obtained at the leaf, plant, and field scales were averaged, as shown in the dashed line in Figure 8. The average weights obtained local peaks in the green, red, and NIR bands, and the peaks corresponded to 540, 660, and 770 nm, respectively. Therefore, the three wavelengths were used as multi-scale sensitive wavelengths.

The ability of individual-scale sensitive wavelengths, multi-scale sensitive wavelengths, and full wavelengths to detect disease severity was compared using KNN and MLR, and the results are shown in Table 6. Among them, 540, 660, and 760 nm are sensitive wavelengths at the leaf scale, 530, 640, and 770 nm are sensitive wavelengths at the plant scale, and 540, 660, and 770 nm are sensitive wavelengths at the field scale. The results of the comparison between KNN and MLR show that KNN outperforms MLR when using the full wavelength for disease class detection and that MLR outperforms KNN when using the sensitive wavelength for disease class detection. The comparison results of KNN show that the classification accuracy of the full wavelength is higher than that of the sensitive wavelength at different scales. This is due to the fact that the full wavelength has more features, which improves disease detection. However, too many features tend to affect the speed of the disease detection model and increase the cost in practical applications. In addition, the results of MLR show that individual-scale sensitive wavelengths can have a high detection accuracy at the current scale, and a decrease in accuracy occurs when

span-scale applications are performed. The multi-scale sensitive wavelengths identified in this study can achieve high and stable classification accuracy at different scales.

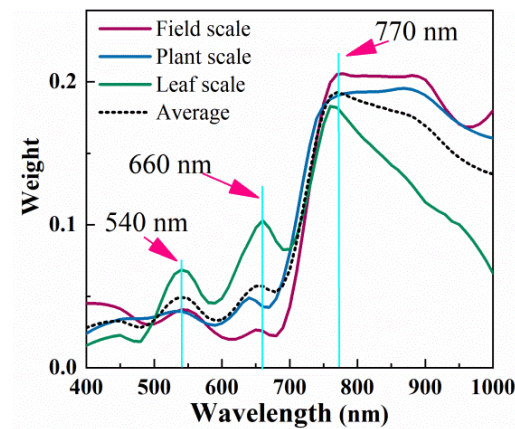


Figure 8. Multi-scale sensitive wavelength selection.

Table 6. Classification results of individual-scale sensitive wavelengths, multi-scale sensitive wavelengths, and full wavelengths.

Scale	Wavelengths (nm)	KNN		MLR	
		OA (%)	Kappa (%)	OA (%)	Kappa (%)
Leaf	540, 660, 760	89.72	86.06	93.83	90.32
	530, 640, 770	91.59	88.62	93.46	91.21
	540, 650, 770	89.10	85.21	92.21	89.50
	540, 660, 770	89.41	85.62	92.21	89.48
	All	98.44	97.91	95.95	94.56
Plant	540, 660, 760	84.38	78.96	90.00	86.58
	530, 640, 770	86.88	82.35	90.62	87.43
	540, 650, 770	83.13	77.25	92.50	89.94
	540, 660, 770	85.62	80.64	91.87	89.10
	All	91.87	89.13	90.00	86.65
Field	540, 660, 760	87.43	83.24	88.57	84.75
	530, 640, 770	88.00	84.02	88.00	83.97
	540, 650, 770	87.43	83.22	88.57	84.74
	540, 660, 770	87.43	83.22	89.14	85.52
	All	89.71	86.27	89.14	85.50

4.4. Comparison of New SI and Traditional SI

In this study, three new SIs of LS, LS-MSSI 1, LS-MSSI 2, and LS-MSSI 3, were constructed by the selected sensitive wavelengths ($\lambda_1 = 770$ nm, $\lambda_2 = 540$ nm, and $\lambda_3 = 660$ nm). The 38 SIs (including the 3 new SIs) were correlated with disease severity levels using Spearman's ranked coefficient, and the results are shown in Table 7. At the leaf scale, 17 SIs—NDVI, AI, MCARI-1, MCARI-2, MTVI-1, MTVI-2, WI, TVI, NWI-1, NWI-2, ARI, PSSRa, LSI, LLSI, LS-MSSI 1, LS-MSSI 2, and LS-MSSI 3—were significantly correlated ($|R| > 0.80$) with disease severity levels. At the plant scale, 10 SIs—MCARI-1, MCARI-2, MTVI-1, MTVI-2, TVI, ARI, LLSI, LS-MSSI 1, LS-MSSI 2, and LS-MSSI 3—were significantly correlated with disease severity levels. At the field scale, 13 SIs—SIPI, RARSa, RARSb, NSI-1, MCARI-1, MCARI-2, MTVI-1, MTVI-2, TVI, PSSRb, LS-MSSI 1, LS-MSSI 2, and LS-MSSI 3—were significantly correlated with disease severity levels. Eight SIs—MCARI-1, MCARI-2, MTVI-1, MTVI-2, TVI, LS-MSSI 1, LS-MSSI 2, and LS-MSSI 3—were significantly correlated with disease severity levels at three scales simultaneously.

Table 7. The correlation coefficient of 38 SIs with disease severity levels.

NO.	SI	Leaf Scale	Plant Scale	Field Scale
1	SR	0.57	0.47	−0.66
2	NDVI	−0.83 **	−0.70	−0.79
3	AI	0.91 **	0.77	0.55
4	SIPI	−0.76	−0.64	−0.80 **
5	DSSI-1	−0.19	0.52	0.68
6	DSSI-2	−0.03	−0.56	−0.04
7	CI	−0.26	−0.11	0.10
8	Chl SI-1	−0.59	−0.45	0.65
9	Chl SI-2	−0.02	0.44	0.38
10	Chl SI-3	−0.61	0.22	0.62
11	RARSa	0.59	0.65	0.83 **
12	RARSb	−0.10	0.49	0.71
13	RARSc	−0.62	−0.62	−0.82 **
14	LHI	−0.47	−0.51	−0.72
15	NSI-1	−0.01	0.17	0.82 **
16	NSI-2	−0.23	−0.02	−0.47
17	PPR	−0.55	−0.50	−0.54
18	PRI	0.76	−0.31	−0.19
19	TCARI	−0.65	−0.76	−0.53
20	MCARI-1	−0.93 **	−0.94 **	−0.92 **
21	MCARI-2	−0.93 **	−0.94 **	−0.91 **
22	MTVI-1	−0.93 **	−0.94 **	−0.92 **
23	MTVI-2	−0.93 **	−0.94 **	−0.91 **
24	PSRI	0.77	0.02	0.11
25	WI	0.88 **	0.51	0.58
26	TVI	−0.95 **	−0.94 **	−0.92 **
27	NWI-1	0.88 **	0.51	0.58
28	NWI-2	0.93 **	0.68	0.65
29	NPCI	0.78	0.75	0.05
30	ARI	0.92 **	0.82 **	0.27
31	PSSRa	−0.83 **	−0.70	−0.76
32	PSSRb	−0.70	−0.59	−0.80 **
33	LSI	0.92 **	0.70	0.59
34	ELSI	0.36	0.20	0.07
35	LLSI	0.87 **	0.80 **	−0.65
36	LS-MSSI 1	−0.91 **	−0.83 **	−0.81 **
37	LS-MSSI 2	−0.91 **	−0.83 **	−0.81 **
38	LS-MSSI 3	−0.95 **	−0.94 **	−0.92 **

Note: ** indicates a significant correlation.

The separability of the significantly correlated SIs was evaluated using the M-statistic value at multiple scales. Figure 9 shows the M-statistic mean, maximum, and minimum values between different disease severity levels. Overall, the mean M-statistic values of all six SIs—MCARI-1, MCARI-2, MTVI-1, MTVI-2, TVI, and LS-MSSI 3—were greater than 1, indicating that they had good separability. At the leaf scale, the M-statistic values of all SIs were greater than 1, indicating that they had good differentiability. In contrast, the mean values of M-statistics of LS-MSSI 1 and LS-MSSI 2 were less than 1 at both plant and field scales, indicating that they did not have good differentiability. In addition, the mean value of the highest M-statistic was obtained for LS-MSSI 3 at the leaf, plant, and field scales, indicating that it has the best separability for all scales. Therefore, LS-MSSI 3 was identified as the final leaf spot multi-scale spectral index (LS-MSSI).

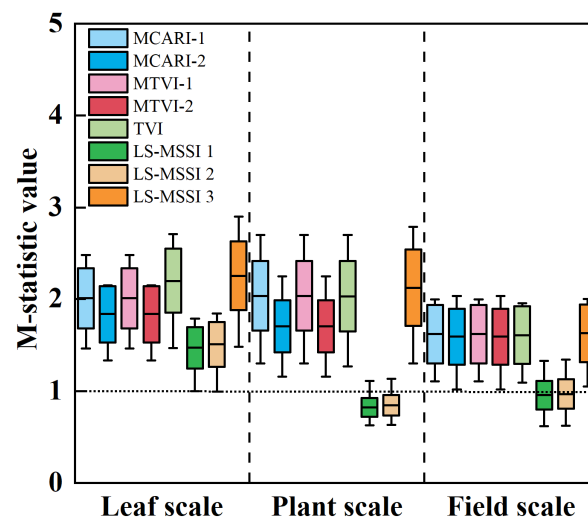


Figure 9. M-statistic values of the significantly correlated SIs.

4.5. Classification Results

KNN and MLR were used to evaluate the ability of six SIs—MCARI-1, MCARI-2, MTVI-1, MTVI-2, TVI, and LS-MSSI—to detect LS severity, and the results are shown in Table 8. From the classification results of KNN, the highest accuracy was obtained for TVI at the leaf scale, with OA and Kappa reaching 93.77% and 91.59%, respectively. At the plant and field scales, LS-MSSI obtained the highest accuracy, with OA reaching 91.25% and 90.29% and Kappa reaching 88.29% and 87.04%, respectively. From the classification results of MLR, at the leaf scale, TVI and LS-MSSI obtained the highest accuracy, with OA and Kappa reaching 93.77% and 91.59%, respectively. At the plant and field scales, LS-MSSI obtained the highest accuracy, with OA reaching 92.50% and 88.57% and Kappa reaching 89.97% and 84.75%, respectively. From the overall classification results, LS-MSSI can achieve the highest accuracy at all three scales simultaneously.

Table 8. Classification results of SIs at multiple scales.

Method	VIs	Leaf Scale		Plant Scale		Field Scale	
		OA (%)	Kappa (%)	OA (%)	Kappa (%)	OA (%)	Kappa (%)
KNN	MCARI-1	89.10	85.23	88.13	84.10	88.00	83.97
	MCARI-2	85.05	79.78	80.00	73.18	85.14	80.17
	MTVI-1	89.10	85.23	88.13	84.10	88.00	83.97
	MTVI-2	85.05	79.78	80.00	73.18	85.14	80.17
	TVI	93.77	91.59	88.13	84.10	87.43	83.23
	LS-MSSI	93.46	91.15	91.25	88.29	90.29	87.04
MLR	MCARI-1	88.47	84.38	88.13	84.11	87.43	83.22
	MCARI-2	85.67	80.65	85.63	80.75	86.86	82.45
	MTVI-1	88.47	84.38	88.13	84.11	87.43	83.22
	MTVI-2	85.67	80.65	85.63	80.75	86.86	82.45
	TVI	93.77	91.59	88.75	84.95	86.86	82.47
	LS-MSSI	93.77	91.59	92.50	89.97	88.57	84.75

5. Discussion

5.1. Analysis of Individual-Scale SI and Multi-Scale SI

To explore the transferability and reliability of the SIs at individual scales for spans-scale disease detection, the SIs at each scale were obtained separately in this study. $LS-MSSI_{Leaf}$, $LS-MSSI_{Plant}$, and $LS-MSSI_{Field}$ were SIs established at the leaf, plant, and field scales. KNN and MLR were used to evaluate the accuracy of SIs at individual scales for detecting disease severity at other scales, and the results are shown in Figure 10.

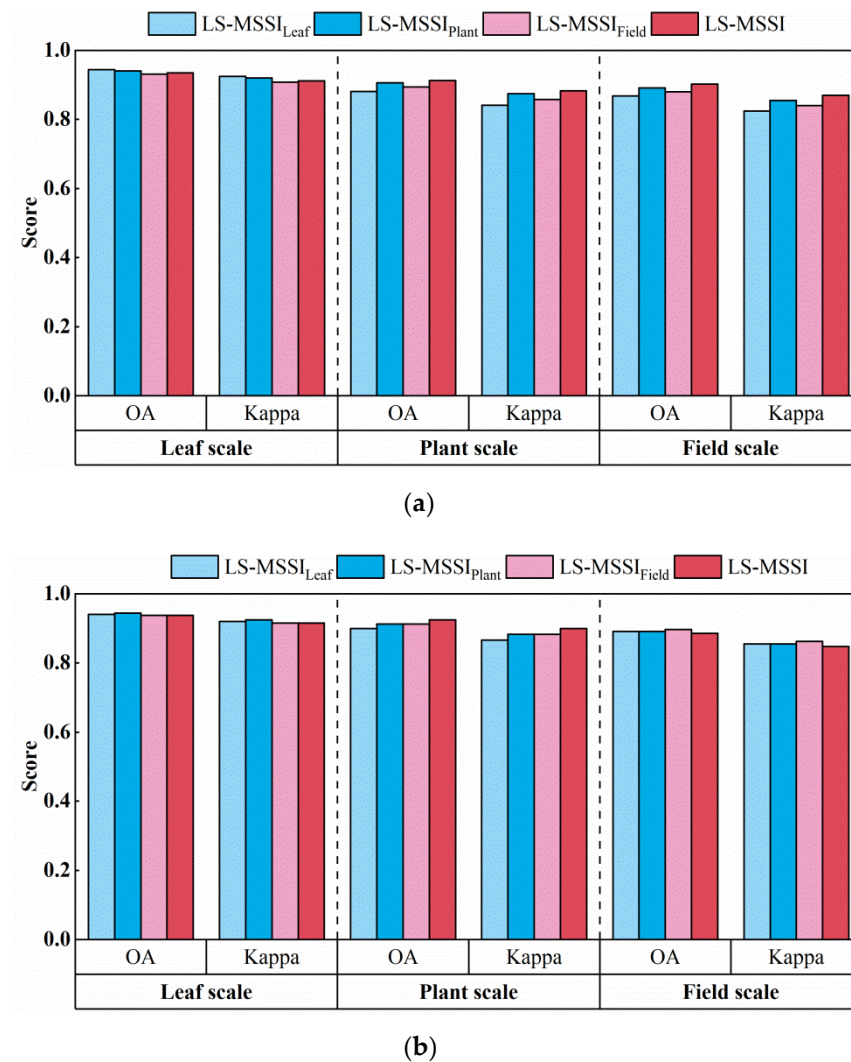


Figure 10. Comparison results of individual-scale SIs and multi-scale SI: (a) KNN; (b) MLR.

From the classification results of KNN shown in Figure 10a, it can be seen that LS-MSSI_{Leaf} obtained high accuracy at the leaf scale, while lower accuracy was obtained at the plant and the field scales. From the classification results of MLR shown in Figure 10b, it can be seen that LS-MSSI_{Field} obtained higher accuracy at the field scale and lower accuracy at the leaf and plant scales. The above results illustrate that the SIs established at individual scales can have a high detection accuracy at their respective scale, while applications at other scales are less effective. The above conclusions are similar to the results of previous studies. For example, the authors of [20] used different SIs for disease detection at the leaf and field scales. The authors of [21] used different SIs for the detection of powdery mildew disease at the leaf and field scales, respectively. Therefore, the SIs determined at individual scales may decrease the accuracy of disease detection in span-scale applications.

Not all SIs applied at different scales can result in a decline in accuracy. The authors of [23] demonstrated that MTVI-1 and the reformed difference vegetation index (RDVI) can detect bacterial spot (BS), target spot (TS), and tomato yellow leaf curl (TYLC) at the leaf and field scales. The authors of [28] created SIs at the leaf scale, and four SIs were verified on the multispectral images obtained at the field scale. The authors of [63] determined the most effective wavelengths at the leaf scale and applied them to multispectral aerial images taken by a UAV. Moreover, similar results were obtained in this study. From the classification results of KNN, it can be seen that LS-MSSI_{Plant} obtained higher classification results at the plant and field scales. In contrast, the accuracy at the leaf scale was slightly

lower than that of $LS-MSSI_{Leaf}$. From the classification results of MLR, it can be seen that $LS-MSSI_{Plant}$ obtained higher classification results at leaf and plant scales, while the accuracy at the field scale was slightly lower than that of $LS-MSSI_{Field}$. The above results suggest that the SIs determined at individual scales can be applied to other scales.

Comprehensive analysis shows that the accuracy of SIs for disease detection determined at individual scales is unstable at other scales. Therefore, this study combined the feature weights obtained at different scales to obtain multi-scale sensitive wavelengths and used the sensitive wavelengths to construct a multi-scale SI. From the results of KNN and MLR, the $LS-MSSI$ was slightly lower than the accuracy of $LS-MSSI_{Leaf}$ and $LS-MSSI_{Plant}$ at the leaf scale and better than the SIs determined at individual scales at the plant scale. $LS-MSSI$ obtained the highest accuracy at the field scale using KNN, while $LS-MSSI$ was slightly less accurate than $LS-MSSI_{Field}$ using MLR. The results show that the $LS-MSSI$ determined at multiple scales has high accuracy, which is conducive to constructing a peanut LS detection model with higher accuracy, stability, and robustness. In practical applications, the detection of peanut LS disease severity at different scales using $LS-MSSI$ can reduce the application cost of the equipment. In addition, this study investigated the variation pattern of spectral reflectance for different disease severity levels from the leaf scale to the plant scale to the field scale and determined the multi-scale SI. It can be inferred that the SI proposed in this study can be used for disease detection at any scale between leaf, plant, and field scales, making the multi-scale SI more applicable in practical applications.

5.2. Analysis of the Proposed New SI and the Traditional SI

According to research [64,65], the detection of different diseases of different crops requires specific sensitive wavelengths. Therefore, the spectral reflectance of peanut LS disease with different disease severity levels was analyzed at the leaf, plant, and field scales, respectively. It can be seen from the results that the sensitive wavelengths at different scales have similarities and are mainly concentrated in the green band, red band, and NIR band. The reason for this is that, when pathogens interact with host plants, color changes and necrosis symptoms lead to the decrease in reflectance in the green band and the increase in reflectance in the red band. The decrease in crop biomass caused by pathogens can reduce reflectance in the NIR band, which is consistent with the results of [56]. Previous studies have shown that the decrease in reflectance in the green band is related to the breakdown of chlorophyll and that the difference in reflectance in the red band may be related to changes in carotenoid and lutein pigments [66]. The decrease in reflectance in the NIR band is mainly influenced by changes in leaf structure and water content [67,68]. In addition, the authors of [69,70] showed that the NIR band is also a sensitive indicator of canopy structure changes.

Meanwhile, as the spatial resolution decreased (leaf scale to plant scale to field scale), the separability in the red and green bands gradually decreased, and the separability in the NIR band gradually increased. This may be because the average reflectance of a region in the field is obtained at the plant and field scales. The mixed information region gradually weakens the separability in the green and red bands [24]. In addition, the reflectance in the NIR band is mainly influenced by leaf shape, transpiration rate, canopy morphology, and plant density variation, making the leaf-scale features different from the plant-scale and field-scale features. From the above, it can be seen that the spectral reflectance at different scales responds to different disease features, and the individual-scale sensitive wavelengths do not allow for comprehensive assessment and detection, which can make the detection accuracy unstable during the spans-scale application. To improve the transferability of features, the peaks of the average weights of the three scales were used as sensitive wavelengths in this study, namely, 540, 660, and 770 nm.

This study constructed three SIs ($LS-MSSI$ 1, $LS-MSSI$ 2, and $LS-MSSI$ 3) by selected sensitive wavelengths. The 38 SIs were correlated with disease severity levels. Eight SIs—MCARI-1, MCARI-2, MTVI-1, MTVI-2, TVI, $LS-MSSI$ 1, $LS-MSSI$ 2, and $LS-MSSI$ 3—were significantly correlated with LS severity levels at all three scales simultaneously, and six

SIs—MCARI-1, MCARI-2, MTVI-1, MTVI-2, TVI, and LS-MSSI 3—with good separability were evaluated using M-statistic values. MCARI and TVI measure photosynthetically active radiation associated with chlorophyll absorption. MCARI-1, MCARI-2, MTVI-1, and MTVI-2 are improved versions of MCARI and TVI. The authors of [20,35] considered TVI as one of the most significant indices for detecting target spot (TS) disease in tomatoes. The results of [56] regarding the detection of LS showed that 12 SIs, such as MCARI, were significantly associated with the DI. The improved detection of the above SIs may be because the diseased parts of the leaves are mainly dark brown or black when the LS occurs in peanut crops. Different physiological symptoms such as leaf discoloration, a curling shape, and sparse leaves appear in the plant canopy, changing the canopy density and green leaf area index [3].

The LS-MSSI proposed in this study and TVI are constructed from three sensitive wavelengths, and their sensitive wavelengths are very close. However, the equations for constructing the spectral index show that TVI uses 550 nm as the most sensitive wavelength, while LS-MSSI uses 770 nm as the most sensitive wavelength. TVI is mainly used to measure photosynthetically active radiation related to chlorophyll absorption. The reflectance variation in the green band, where 550 nm is located, is closely related to chlorophyll content. Our study found hyperspectral reflectance of different disease severity levels was different in green, red, and NIR bands. Among them, the NIR band is the band with the greatest variability. Therefore, LS-MSSI and TVI have similar sensitive wavelengths, while there are differences in the construction methods. In both KNN and MLR, TVI obtained high accuracy at the leaf scale. However, at plant and field scales, KNN and MLR showed lower accuracy of TVI than LS-MSSI. Our results showed that the differences in the red and green bands gradually decreased, and the differences in the NIR region gradually increased with the change from leaf scale to plant scale to field scale. TVI is sensitive to chlorophyll content, resulting in a poor ability to detect crop disease severity at the plant and field scale. Therefore, a comprehensive comparison showed that LS-MSSI and TVI had similar disease detection abilities at the leaf scale. However, the accuracy of LS-MSSI was better than TVI for detecting the disease severity at the plant and field scales.

The LS-MSSI proposed in this study can obtain high accuracy at all three scales simultaneously, and its results are superior to other SIs. The results also show that the highest accuracy was obtained at the leaf scale and the lowest was obtained at the field scale. These results may be due to the hyperspectral reflectance that can be obtained under an ideal environment in the laboratory. In contrast, the acquisition of hyperspectral reflectance in the field is easily affected by weather, light, and the environment, resulting in lower accuracy and stability at the plant and field scales than at the leaf scale.

6. Conclusions

When diseases infect plants, photosynthesis, biochemical indexes, and the physical structure of plants will change, thereby affecting the absorption of light on the plant surface. The spectral difference between healthy and diseased plants is the key to identifying specific diseases. Determining the sensitive wavelengths with a large difference, high separability, and strong expansibility can effectively improve the accuracy and stability of disease identification. Therefore, this study explored the sensitive wavelengths at multiple scales to construct the SI of specific LS.

In this study, the hyperspectral reflectance of peanut LS with different severity levels was collected at the leaf, plant, and field scales. The difference and separability of wavelengths were evaluated considering mean, variance, and dispersion. The feature weights of wavelengths at different scales were obtained using Relief-F, and sensitive wavelengths were obtained by averaging the feature weights at three scales. The SIs were constructed using sensitive wavelengths. Correlation analysis and M-statistics values were performed between 35 commonly used SIs and 3 new ones, and 6 SIs were finally identified for detecting LS severity. KNN and MLR evaluated the ability of SIs to detect LS severity. The results show that the LS-MSSI proposed in this study had better accuracy, reaching 93.77% and

91.59% for OA and Kappa at the leaf scale, respectively. At the plant scale, OA and Kappa reached 92.50% and 89.97%, respectively. At the field scale, OA and Kappa reached 90.29% and 87.04%, respectively.

The above conclusions show that the LS-MSSI determined in this study can be used to detect LS severity at multiple scales. The LS-MSSI considered three sensitive wavelengths, which were selected in an experimental environment and tested with a specific cultivar. In future work, we will validate the proposed SI under different conditions. We also need to consider whether the SI proposed in this study can distinguish between other biotic and abiotic stresses.

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