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A New Disease Index Based on Multi-Spectra of UAV to Estimate Cotton Disease

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Abstract: *Verticillium* wilt is a significant disease that affects cotton plants, which can lead to stunted growth and reduced yield. To address this, a multi-spectral comprehensive monitoring disease index model is developed using an Unmanned Aerial Vehicle (UAV) to monitor the severity of cotton *Verticillium* wilt. First, multi-spectral dates were collected from Hexacopter (HY-6X) and the phenotype disease grade of cotton plants at monitoring sites was investigated. Then, a new indicator for cotton diseases was established using the correlation coefficient method and optimal index factor method and the regression models for four types of cotton diseases were established. The results show that cotton plants with different severity of *Verticillium* wilt have different spectral characteristics in the near-infrared and visible light bands. As the disease severity increased, the spectral reflectance of the cotton canopy increased from 470-656nm. Combined Difference Vegetation Index (DVI) with B3-B5-B8, a new index, UAV multispectral comprehensive monitoring disease index is created. Taking the comprehensive indicator as the independent variable, a regression model including multiple-linear regression, partial least squares regression, principal component analysis and support vector machine regression is established. The results show the support vector machine regression model has the highest accuracy (prediction set $R^2 = 0.91$, RMSE = 0.07; validation set $R^2 = 0.89$, RMSE = 0.08; and the linear relationship is significant at the 95% level). Compared with other indicators, using UAV for monitoring cotton disease severity will be the optimal model for motoring the severity of cotton diseases.

Keywords: Cotton, Disease, UAV, Multi-Spectral, Comprehensive Monitoring Index of Disease, Regression Models

Introduction

Cotton *Verticillium* wilt is a major disease of cotton and is one of the diseases that restrict cotton production. Song *et al*. (2023) found that a reduction or no yield would seriously affect the production efficiency of cotton and bring great harm to the cotton industry. Cotton *Verticillium* wilthas become one of the most preventable diseases in the world.

Jing *et al*. (2021) thought that traditional crop disease monitoring methods mainly rely on professional and technical personnel to investigate, analyze and determine the severity of the disease in the field, which is time-consuming, laborious, highly subjective and has poor timeliness, making it difficult for large-scale investigation (Jing *et al*., 2021; Manowarul *et al*., 2023). Compared with the deficiencies of traditional crop disease monitoring methods, UAV multispectral technology is fast, non-destructive, efficient and objective, which can make up for the deficiencies of traditional monitoring points and provide a reference for large-scale crop disease monitoring by satellite remote sensing.

Using hyper-spectral data, multispectral data and satellite images, (Chen *et al*., 2007; Chen *et al*., 2011) monitored the Crop diseases and analyzed the characteristics of spectral position variables (Hu *et al*., 2022; Chen *et al*., 2007) after crop diseases. They include "blue shift" and "red shift" in the position of red edge and spectral characteristics absorption parameters, such as the position of absorption peak, valley, width, depth and area. The screening and sensitivity characteristics of vegetation index, including vegetation index, can better reflect the change characteristics after disease, as well as the combination of sensitive bands. The qualitative and quantitative identification of crop diseases can be realized by establishing the monitoring model of crop disease severity. The monitoring models for crop disease severity can be generally divided into two categories: Statistical models and artificial intelligence models (Dhiman *et al*., 2023). Song thought that statistical models were intuitive and simple, such as linear and nonlinear models, but their accuracy was limited and the autocorrelation was relatively strong when the sample size was large (Song *et al*., 2022). Artificial intelligence models are highly accurate, but complex, such as artificial neural network models, support vector machine models and deep learning algorithm models. Different parameters need to be selected and input. Chen *et al*. (2012) improved the algorithm accuracy, which is subjective to a certain extent and has a certain impact on the stability of results. They also established a statistical linear model based on hyperspectral data and a model based on an IKNOS image using a partial least squares regression method to quantitatively estimate the severity of cotton *Verticillium* wilt disease.

There are also studies on crop disease estimation using digital images, thermal infrared images, fluorescence imaging and radar images. Shi *et al*. (2020) used the relationship between the RGB-to-HIS spatial transformation of cotton canopy images and the vegetation index of typical diseases to identify features sensitive to changes in *Verticillium* wiltsymptoms through the Relief-F algorithm and established a logarithmic model for disease monitoring. Calderón *et al*. (2013) used laser-induced fluorescence imaging to monitor Verticillum wilt of citrus. Lan *et al*. (2022) reviewed the research progress of remote sensing monitoring and prediction of crop diseases and insect pests.

Previous research on crop diseases has been carried out by using different remote-sensing data sources. They mainly focused on wheat rust, rice spike neck plague, citrus *Verticillium* wilt and other diseases. There is no systematic report on the prediction of *Verticillium* wilt severity by regression model based on the new UAV multi-spectral monitoring comprehensive index.

In recent years, studies on monitoring crop diseases mainly use UAV remote sensing. Yu *et al*. (2021) using the fusion of hyperspectral imaging data of UAV and laser radar data accurately evaluated the damage rate of pine forest branches in the early monitoring of pine shoot beetles. Dang *et al*. (2020) obtained UAV-based visible radish wilt image data, segmented the images using a linear spectral clustering super-pixel algorithm and constructed a Rad RGB model to classify different radish, soil and plastic film regions. Xavier *et al*. (2019) used multi-spectral sensors to obtain multi-spectral images of different pest and disease stress areas, extracted spectral information and established classification models to successfully identify pests and diseases in cotton wilt stress areas. Pan *et al*. (2021) classified healthy wheat, yellow rust wheat and bare soil in UAV images based on the PSP Net semantic segmentation model and the recognition accuracy reached 98%. Kong *et al*. (2020) established the UAV hyperspectral vegetation index combination based on the random forest method and realized the monitoring of rice spike neck blast; the prediction set accuracy was 90%. Zhang *et al*. (2020) proposed a rice disease ratio method based on UAV multi-spectral images and established a corresponding model for rice leaf blasts based on the support vector machine algorithm.

In this study, taking the field of cotton *Verticillium* wilt as the research object, a new UAV multi-spectral monitoring comprehensive disease index was established and different types of regression models were constructed to estimate the severity of *Verticillium* wilt. It could provide a theoretical basis for the quantitative and accurate identification of cotton field diseases by UAV multi-spectral remote sensing and provide a reference for the quantitative monitoring of similar crop diseases and pests by UAV multi-spectral remote sensing. Our main contributions are as follows:

1. The multi-spectral changes of cotton *Verticillium* wilt canopy monitored by UAV were significant in different degrees. Especially at 710-950 nm, the spectral curves of cotton fields with different degrees of disease changed significantly
2. DVI was the optimal vegetation index for UAV multi-spectral identification of cotton *Verticillium* wilt canopy with different severity
3. Four regression models were established based on B-RBDVI, among which the accuracy of the support vector machine regression model was the highest

Materials and Methods

Test Site Overview and Test Design

This study was conducted at the cotton *Verticillium* wiltnursery of Xinjiang academy of agricultural Reclamation sciences in Shihezi (44°32′N, 85°97′E), Xinjiang. The soil is grey desert soil, with an organic matter of 21.3 g/kg, total nitrogen of 0.2%, available phosphorus of 55.5 mg/kg and available potassium of 664.1 mg/kg. The cotton, Xinluzao 8 was sown on April 17, 2020 and April 20, 2021, respectively. The planting mode was drip irrigation under film, with a width and narrow row (66+10) cm of machine-harvested cotton, a plant spacing of 9.6 cm and a planting area of approximately 1.45 hm^2. The plot was divided into 3 plots (0.49 hm^2 for each plot), that is, 3 replicates. The irrigation was about 5775 m^3/hm^2 in the whole cotton growth period. It was applied with pure N 420, P2O5 210 and k^2 O 155 kg/hm^2 with water and no base fertilizer. There were a total of 66 ground monitoring points arranged in a network format, with 22 monitoring points in each repeated plot. Each plot was equipped with 3 or more replicates of disease severity. Each monitoring point was marked with a measuring instrument-Global Positioning System (GPS). Other cultivation techniques are managed according to the high yield of cotton, in Fig. 1.

Test Site Overview and Test Design

The UAV is a Hexacopter (HY-6X), with a weight of 4.1 kg, a flight control voltage of 21.5 V~23 V, an endurance time of about 25 min and a maximum load of 3.0 kg. A multi-spectral camera with 12 channels was installed under the UAV and the camera is equipped with 1280×1024 pixel Complementary Metal-Oxide-Semiconductor (CMOS), with a focal length of 9.6 mm in each of 12 bands. The characteristics of Micro MCA12 snap in Table 1.

The UAV aerial photography operation was carried out from 11:00-13:00, under high visibility and low wind speed on clear days, with a flying altitude of 100 m and a flying speed of 5 ms^{1}. The lateral overlap rate of heading was 80% and the flight overlap rate also was 80%, with a multi-spectral resolution of 10-20 nm and a spatial resolution of about 5.5 cm. The acquisition time of UAV multi-spectral images in the test field was: June 30 (bud stage), July 15 (blessing and boll-forming stages), August 10 (blossing and boll-forming stages), August 23 (blossing and boll-forming stages) and September 17 (boll opening stages), 2020; July 1 (bud stage), July 19 (blossing and boll-forming stages), August 11 (blossing and boll-forming stages) and August 25 (boll opening stages), 2021.

Methods of Disease Investigation and Classification

After the UAV multi-spectral image data collection was completed, the phenotype of cotton plants at the monitoring sites was immediately investigated and the disease grade was performed according to the disease grade classification standard of "technical specification for evaluation of resistance to pests and diseases of cotton, part 5: *Verticillium* Wilt" (GB/T 22101.5-2009) (Zhang *et al*., 2020). Then, disease severity (b0-b4) was divided according to the disease index (Huang *et al*., 2023). Details are shown in Table 2. Meanwhile, the incidence of the cotton canopy in the monitoring sites was recorded by camera.

Data Processing and Analysis

Multi-spectral Image Pretreatment of UAV

Image stitching, overlay, radiation correction and accuracy (over 95%) correction were performed in pix 4D mapper software. Using the ENVI 5.3 software, based on the characteristics of UAV multi-spectral data combined with previous studies, 15 vegetation indices were selected (Table 3).

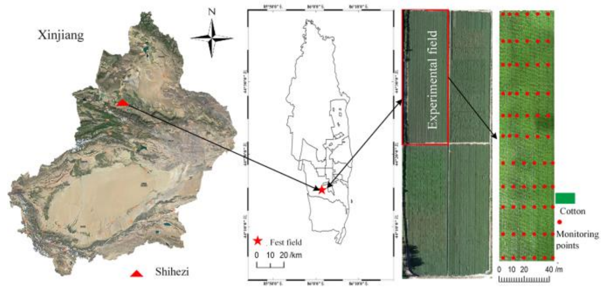


Fig. 1: Schematic diagram of test area

Table 1: Band characteristics of micro MCA12 snap

Bands	Wavelength-width	Bands	Wavelength-width
B1	470-10	B07	760-10
B2	515-10	B08	800-10
B3	550-10	B09	830-10
B4	610-10	B10	860-10
B5	656-10	B11	900-20
B6	710-10	B12	950-20

Table 2: Classification standard of cotton *verticillium* wilt disease severity

Disease severity	Disease index (%)	Disease division standard
b0 (Health)	0	No diseased leaves
b1 (Slight)	$0<DI\leq 25$	Less than 25% of leaves showed symptoms
b2 (Moderate)	$25<DI\leq 50$	25-50% of leaves showed symptoms
b3 (Serious)	$50<DI\leq 75$	50~75% of leaves showed symptoms, some leaves wither and fall
b4 (Critical)	$75<DI\leq 100$	More than 75% of leaves were infected, with the majority showing brown spot

Optimal Band Combination Selecting

The optimal band combination was selected based on the best index factor (optimum index factor, R_{OIF}) and calculated by the following formula (Song *et al*., 2022):

$$R_{OIF}=\frac{S_1+S_2+S_3}{R_{12}+R_{13}+R_{23}} \tag{1}$$

where, S_1, S_2 and S_3 represent the standard deviation of any three multi-spectral bands and R_{12}, R_{13} and R_{23} are the corresponding Pearson (Pearson) correlation coefficients between any three bands. The 12 bands could derive 220 band combinations that are made up of three bands. Gray scale variance and correlation were analyzed in SPSS 12.0 software to calculate R_{OIF}. The top 15 band combinations with the largest R_{OIF} values were selected. The larger the R_{OIF} value, the higher the quality and quantity of band combination information and the better the correlation.

Table 3: Vegetation indexes related to crop diseases and insect pests

Name of vegetation index	Abbreviation	Formula	Reference
Normalized differential vegetation index	NDVI	$(R_{800}-R_{656})/(R_{800}+R_{656})$	He *et al*. (2018)
Ratio vegetation index	RVI	R_{800}/R_{656}	Hikishima *et al*. (2010)
Differential vegetation index	DVI	R_{800}-R_{656}	Huang *et al*. (2019)
Re normalized differential vegetation index	RDVI	$(R800-R656)/\sqrt{R800+R656}$	Jonas and Gunter (2007)
Green band normalized differential vegetation index	GNDVI	$(R_{800}-R_{550})/(R_{800}+R_{550})$	Kerkech *et al*. (2018)
Red edge normalized difference vegetation index	RENDVI	$(R_{760}-R_{710})/(R_{760}+R_{710})$	Kumar *et al*. (2012)
Normalized difference greenness index	NDGI	$(R_{550}-R_{656})/(R_{550}+R_{656})$	Jia *et al*. (2012)
Triangle vegetation index	TVI	$0.5*[120*(R_{800}-R_{550})-200*(R_{656}-R_{550})]$	Li *et al*. (2012)
Soil adjusted vegetation index	SAVI	$1.5*(R_{800}-R_{656})/(R_{800}+R_{656}+0.5)$	Lin *et al*. (2016)
Optimize soil-adjusted vegetation index	OSAVI	$(R_{800}-R_{656})/(R_{800}+R_{656}+0.16)$	Elkington (1987)
Modified soil adjusted vegetation index	MSAVI	$0.5*\left[(2*R_{800}+1)-\sqrt{(2*R_{800}+1)^2-8(R_{800}-R_{656})}\right]$	Mcfeeters (1996)
Anthocyanin reflex index	ARI	$1/R_{550}-1/R_{710}$	Mirik *et al*. (2012)
Enhanced vegetation index	EVI	$2.5*\{(R_{800}-R_{656})/(R_{800}+6*R_{656}-7.5*R_{550}+1)\}$	Penuelas and Filella (1998)
Normalized differential water index	NDWI	$(R_{950}-R_{550})/(R_{950}+R_{550})$	Phadikar *et al*. (2012)
Water band index	WBI	R_{900}/R_{950}	Naidu *et al*. (2009)

Modeling Method and Evaluation Indexes

Four modeling methods: Multiple Linear Regression (MLR), Partial Least Squares Regression (PLSR), Principal Component Analysis regression (PCA) and Support Vector Machine regression (SVM) were used. In 2020, 55 samples were used to establish patterns and in 2021, 56 samples were used to test patterns. The larger the R^2, the smaller the RMSE, indicating the higher the accuracy and reliability of the model.

Results and Discussion

Multi-Spectral Characteristics of UAV in the Canopy of Cotton with Different Disease Severity

The lighter the degree of disease in cotton fields, the higher the spectral reflectance value (vertical axis) in Fig. 2. Compared with b0, the canopy spectral reflectance of cotton with different disease severity (b1-b 4) changes greatly (Fig. 2). In the range of visible band (470-656 nm), the reflectance of the canopy of b1-b 4 remains unchanged in the band of 470-515 nm; the reflectance of the canopy of b0-b 4 increased in 515-550 nm and reached its peak at 550 nm; the reflectance of b0-b4 decreases within 610-656 nm. In the red sideband range (710-760 nm), the canopy reflectance of b0~b4 increases significantly and the reflectance value gradually decreases with the disease severity (b0-b4) increased. In the range of near-infrared band (800-950 nm), the canopy spectral reflectance of cotton with different disease severity (b0-b4) was basically stable and the spectral reflectance values rank as b0>b1>b2>b3>b4. The above results indicate that the multi-spectral image characteristics (spectral reflectance) of UAV change greatly with different cotton *Verticillium* wilt and can effectively reflect the cotton diseases.

Established a New Comprehensive Monitoring Disease Index from Multi-Spectrum Data of UAV

Through extracting the spectral reflectance of cotton canopy with different disease severity at the monitoring points, the vegetation index was constructed and its correlation with disease severity was analyzed (Table 4). The results show that NDWI, WBI and NDGI have a positive correlation with cotton disease severity and the correlation coefficient is small. NDVI, RVI, DVI, RDVI, GNDVI, RENDVI, TVI, SAVI, OSAVI, MSAVI, ARI and EVI have a significant negative correlation with cotton disease severity and DVI has the strongest negative correlation with cotton disease severity, with a correlation coefficient of -0.86. Therefore, DVI could be initially used as the optimal vegetation index for optimum vegetation index for identifying the severity of cotton disease.

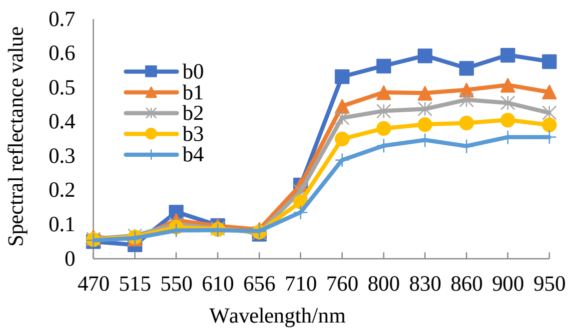


Fig. 2: Multi-spectral characteristic curve of UAV for cotton *Verticillium* wilt of different severity

Table 4: Correlation between spectral vegetation indexes and disease severity of cotton canopy

Vegetation index	Correlation coefficient	Order	Vegetation index	Correlation coefficient	Order
DVI	-0.86**	1	RENDVI	-0.49**	9
TVI	-0.73**	2	NDVI	-0.37**	10
RDVI	-0.71**	3	EVI	-0.36**	11
SAVI	-0.70**	4	NDGI	0.30**	12
MSAVI	-0.68**	5	RVI	-0.27**	13
GNDVI	-0.67**	6	WBI	0.16**	14
ARI	-0.56**	7	NDWI	0.12*	15
OSAVI	-0.55**	8	-	-	-

Note: ** and *indicate extremely significant difference ($p<0.01$) and significant ($p<0.05$)

Table 5: The top 15 band combinations of OIF values

No	Band combination	OIF value	Number	Band combination	OIF value
1	B3,B5,B8	153.44	9	B1,B6,B10	81.88
2	B4,B6,B8	132.26	10	B1,B7,B8	80.98
3	B4,B6,B9	128.28	11	B1,B6,B8	79.61
4	B4,B6,B10	109.57	12	B1,B6,B9	79.21
5	B2,B3,B8	097.48	13	B4,B5,B9	73.56
6	B4,B5,B8	091.76	14	B3,B6,B9	70.73
7	B3,B6,B8	089.27	15	B2,B8,B11	67.83
8	B3,B5,B9	083.71	/	/	/

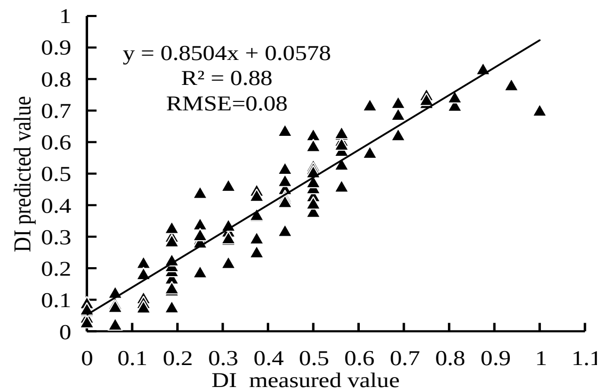
According to the correlation coefficient results in Table 2, the optimal band combination of cotton disease severity was further selected with the help of OIF value (Table 5). Table 3 shows the OIF values of the top 15 bands between 67.83-153.44 and the top three bands are [B (3-5-8)], [B (4-6-8)] and [B (4-6-9)]. Since the combination of B3, B5 and B8 corresponds to the largest OIF value; the wavelength of this band combination corresponds to 550, 656 and 800 nm respectively, representing the green light band, red band and red sideband. It is a sensitive band for vegetation identification and consistent with the analysis results of the above correlation coefficients and can better reflect the incidence of cotton disease severity. Therefore, based on the reflectance value of the optimal spectral band B3-B5-B8 for cotton diseases, [B (3-5-8)] could be used as the best band combination for UAV multi-spectral data and a new integrated multi-spectral disease monitoring index to B-RBDVI (RB (3-5-8) + DVI) could be created to provide a basis for UAV multi-spectral data to monitor cotton diseases.

Establishment of a Cotton Disease Model Using UAV Multi-Spectrum Data

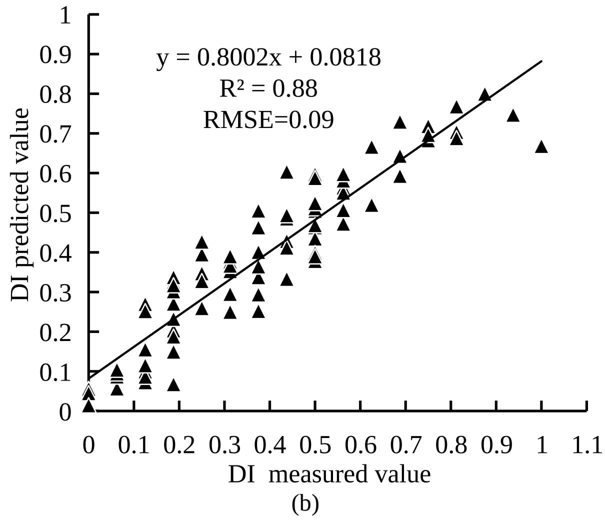
Using the multi-spectral disease monitoring index B-RBDVI (RB (3-5-8) + DVI) as the independent variable, four estimation models of cotton disease severity are established, namely the multiple linear regression model, partial least squares regression model, principal component analysis regression model and support vector machine regression model (Table 6). Table 6 shows that the complexity of the four regression monitoring models is similar. According to the accuracy evaluation index of the prediction set, the difference between R^2 and RMSE values is small. All R^2 exceeds 0.88(0.880-0.912) and RMSE is less than 0.08 (0.065-0.079), which can be used to accurately estimate the disease severity of cotton canopy. Among them, the support vector machine regression model has the highest accuracy (prediction set R^2 = 0.912, RMSE = 0.065), followed by the multivariate linear regression model (prediction set R^2=0.912, RMSE = 0.065) and then the partial least squares regression model and principal component analysis model, with the same accuracy of the prediction set (prediction set R^2 = 0.879, RMSE = 0.079).

Table 6: Cotton *verticillium* severity monitoring model

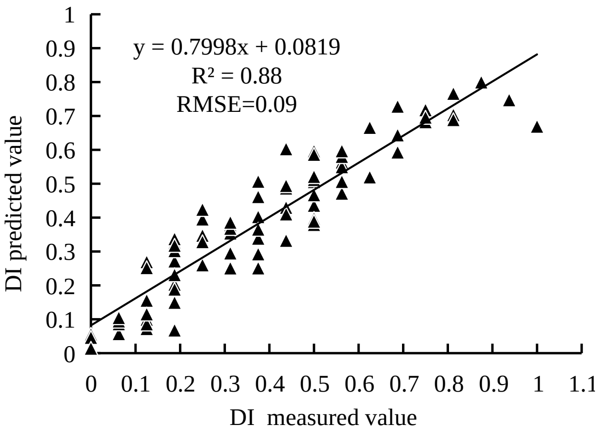
Variable	Model	Model expression	R^2	RMSE
	Multiple linear regression models	y = 1.694-4.106*RB3+ 2.313*RB RB5-2.40RB8-0.272*DVI	0.880	0.078
	Partialleast squaresregression model	y = 1.729-0.427*RB3+ 0.583*RB RB5-3.064*RB8-0.386*DVI	0.879	0.079
RB (3-5-8) +DVI	Principal component analysis	y = 1.723-0.442*RB3+ 0.619*RB5-3.062*RB8-0.344*DVI	0.879	0.079
	Vectormachine regression model	/	0.912	0.065



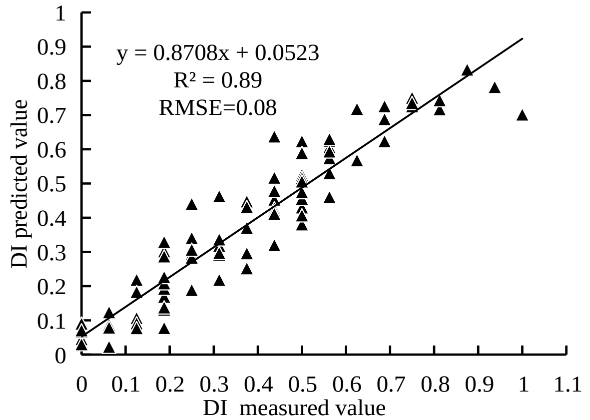
(a)



(b)



(c)



(d)

Fig. 3: Correlation between the measured and predicted values of different monitoring models; (a) Correlation between the measured and predicted values of the multiple linear regression models; (b) Correlation between the measured and predicted values of the partial least squares regression model; (c) Correlation between the measured and predicted values of the regression model by principal component analysis; (d) Correlation between the measured and predicted values of the support vector machine regression model

Verification of the Cotton Disease Model by Multi-Spectrum Data of UAV

To verify the reliability of the four prediction models based on B-RBDVI (RB (3-5-8) + DVI), the four tested regression models from B-RBDVI are established and verified. The correlation between the measured values and predicted values of the verified models is Fig. 3.

Figure 3, the four test regression models of B-RBDVI have high accuracy, with R^2 higher than 0.88 and RMSE lower than 0.09. The validation accuracy and reliability of the support vector machine regression mode of B-RBDVI are the highest, with $R^2 = 0.89$ and RMSE = 0.08. The multiple linear regression model of B-RBDVI is followed, with $R^2 = 0.88$ and RMSE = 0.08. The accuracy and reliability of the partial least squares regression model and principal component analysis regression model of B-RBDVI are basically the same, (which are inferior to the support vector machine regression mode and multiple linear regression model), with the validation set $R^2 = 0.88$, RMSE = 0.09. Therefore, the support vector machine regression model of B-RBDVI (RB (3-5-8) + DVI) can be used as the optimal model for monitoring the cotton disease severity.

Using the comprehensive index, the statistical method and the mathematical method are combined to realize the detection of cotton *Verticillium* wilt, improving the monitoring accuracy. It is found that the UAV multi-spectral reflectance of cotton disease decreases in the visible band and increases in the near-infrared band after the occurrence of *Verticillium* wilt. This is consistent with the results of near-earth hyperspectral remote sensing monitoring (Hu *et al*., 2022). The reason may be that the physiological and biochemical parameters of cotton plants are changed after being subjected to *Verticillium* wilt pathogen stress, leading to changes in external morphology and canopy parameters. The main symptoms are water loss, LAI, coverage and biomass reduction (Song *et al*., 2022), which leads to significant changes in the spectral response characteristics within specific bands (Hu *et al*., 2022; Chen *et al*., 2007). At the same time, cotton plants are also affected by other factors (such as soil type, weather information, geographical factors, multiple stresses, etc.,) in the process of *Verticillium* wilt infection.

When estimating the severity of cotton *Verticillium* wilt by using near-ground hyper-spectrum, the optimal vegetation index DVI from UAV multispectral data to monitor cotton *Verticillium* wilt were consistent with the research results by Chen *et al*. (2007) It is verified that the optimal vegetation index DVI of near-earth hyperspectral and UAV multispectral is verified to be consistent with the results of cotton *Verticillium* wilt. It provides a reference for data normalization of remote sensing monitoring platforms (usually with different spectral resolution, temporal resolution and spatial resolution). Wang *et al*. (2021) studied the differences and similarities in the vegetation index (NDVI, RVI, DVI) of cotton damage prediction and screening by hail. Wang *et al*. (2021) also selected the same vegetation index DVI, which is consistent with ours. Wang *et al*. (2021) also selected the vegetation index RVI and DVI, which are different from ours. It may be that the changes in the cotton canopy after a hail disaster are similar to the cotton canopy after disease, but the spectral characteristics are different. The grayscale standard deviation method and correlation analysis method are combined to select the optimal band combination. The results of the selected optimal band group (B3-B5-B8) are inconsistent with those of (Si *et al*., 2022) (the optimal band was B1-B6-B12). The reason may be that here cotton plants and bare soil of different severity are mainly concerned. Si *et al*. (2022) mainly focused on trees, bare soil and vegetation. In this study, B-RBDVI (RB(3-5-8)+ DVI), a newly established multispectral of UAV disease monitoring index, is used as the parameter of the estimation model for *Verticillium* wilt and a cotton *Verticillium* wilt severity model was established based on the newly established index.

The verification results show that the support vector machine regression monitoring model has the highest accuracy. Due to the different properties of models, their accuracy and reliability are also different. The accuracy and reliability of the established model are consistent with the cotton *Verticillium* wilt severity monitoring model (Jing *et al*., 2021). The results are more accurate than that of Liu *et al*. (2009), who used the NDVI index to build a model for wheat disease prediction and the accuracy R^2 reached 0.61. The possible reason is the modelling parameter used by Liu *et al*. (2009) is a single index NDVI with a modeling sample of 26. The prediction object is wheat stripe rust which is caused by different index types, modeling quantities and disease types. Compared with the research on the prediction methods of cotton mite damage in Xinjiang (Wang *et al*., 2017), the accuracy of the prediction model was improved to 96.84%, which was slightly higher than ours. However, they believe that the RVM model based on remote sensing meteorological data has the best prediction performance, with an accuracy of 85.7%, slightly lower than ours. It can be seen that different types of pests and diseases, different types of remote sensing and ground data sources and different types of models lead to different effects of model prediction and estimation.

There are still some limitations: Due to the limited number of bands used in the UAV multi-spectral sensor, the band accuracy and band screening of 12 bands are limited. To improve the accuracy of the model, it is necessary to further optimize the band screening algorithm and constantly improve the monitoring accuracy of the model. Considering many uncertain factors in field experiments, a comprehensive consideration of multiple factors (such as soil type, weather information, geographical factors, multiple stresses, etc.,) is needed in the future research process to verify the accuracy of the monitoring model. To improve the estimation accuracy of the model, these factors should be taken into account as independent variables to increase the universality of the model.

Conclusion

In this study, the multispectral image data of UAV and ground disease survey data were used to estimate the severity of *Verticillium* wilt in cotton and the severity of diseases in cotton fields was estimated. The main conclusions were as follows.

The multi-spectral changes of cotton *Verticillium* wilt canopy monitored by UAV are obvious in different degrees. The spectral reflectance of the cotton canopy increased slightly at 470~656 nm and decreased slightly at 710~950nm with the increase in disease severity.

DVI ($|r| = 0.86$) was the best vegetation index to identify cotton *Verticillium* wilt canopy with different severity by multi-spectral of UAV, B3- B5-B8 (550-656-800 nm) was the optimal band combination and combination on DVI and B3-B5-B8, a new comprehensive monitoring index of disease, namely BRBDVI (RB (3-5-8) + DVI) was established to estimate cotton *Verticillium* wilt.

Four regression models were established on the base of B-RBDVI, among the regression models, the support vector machine regression model had the highest monitoring accuracy (prediction set $R^2 = 0.91$, RMSE = 0.07; Validation set $R^2 = 0.89$, RMSE = 0.08).

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Author's Contributions

Bing Chen and Jing Wang: Contributed equally to the article. Designed and performed the field trials, analyzed the spectral data and prepared the paper.

Qiong Wang: Corresponding author, complete the spectral data acquisition and analysis and revised the manuscript.

Taijie Liu and Yu Yu: Designed and performed the field trials, analyzed the spectral data and prepared the paper.

Yong Song, Zijie Chen and Zhikun Bai: Participated in collecting the materials related to the experiment, including cotton field cultivation, field disease monitoring, ground survey data acquisition and analysis.

Ethics

The study did not involve human or animal subjects and had no ethical issues.

Data Availability Statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

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