Summer maize LAI retrieval based on multi-source remote sensing data

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Abstract: Leaf Area of Index (LAI) refers to half of the total leaf area of all crops per unit area. It is an important index to represent the photosynthetic capacity and biomass of crops. To obtain LAI conditions of summer maize in different growth stages quickly and accurately, further guiding field fertilization and irrigation. The Unmanned aerial vehicles (UAV) multispectral data, growing degree days, and canopy height model of 2020-2021 summer maize were used to carry out LAI inversion. The vegetation index was constructed by the ground hyperspectral data and multispectral data of the same range of bands. The correlation analysis was conducted to verify the accuracy of the multispectral data. To include many bands as possible, four vegetation indices which included R, G, B, and NIR bands were selected in this study to test the spectral accuracy. There were nine vegetation indices calculated with UAV multispectral data which were based on the red band and the near-infrared band. Through correlation analysis of LAI and the vegetation index, vegetation indices with a higher correlation to LAI were selected to construct the LAI inversion model. In addition, the Canopy Height Model (CHM) and Growing degree days (GDD) of summer maize were also calculated to build the LAI inversion model. The LAI inversion of summer maize was carried out based on multi-growth stages by using the general linear regression model (GLR), Multivariate nonlinear regression model (MNR), and the partial least squares regression (PLSR) models. R^2 and RMSE were used to assess the accuracy of the model. The results show that the correlation between UAV multispectral data and hyperspectral data was greater than 0.64, which was significant. The Wide Dynamic Range Vegetation Index (WDRVI), Normalized Difference Vegetation Index (NDVI), Ratio Vegetation Index (RVI), Plant Biochemical Index (PBI), Optimized Soil-Adjusted Vegetation Index (OSAVI), CHM and GDD have a higher correlation with LAI. By comparing the models constructed by the three methods, it was found that the PLSR has the best inversion effect. It was based on OSAVI, GDD, RVI, PBI, CHM, NDVI, and WDRVI, with the training model's R^2 being 0.8663, the testing model's R^2 being 0.7102, RMSE was 1.1755. This study showed that the LAI inversion model based on UAV multispectral vegetation index, GDD, and CHM improves the accuracy of LAI inversion effectively. That means the growing degree days and crop population structure change have influenced the change of maize LAI certainly, and this method can provide decision support for maize growth monitoring and field fertilization.

Keywords: maize, UAV multispectral, leaf area of index, growing degree day, canopy height model, vegetation index
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1 Introduction

Leaf area index (LAI) refers to half of the total leaf areas of all crops per unit area[1]. It is an important indicator of crop photosynthesis capacity and biomass. LAI is also used to monitor changes in crop growth and yield. So it was regarded as one of the important agronomic parameters[2]. As China's main food and feed crop, maize is vital to national food security and economic regulation. How to obtain the changes in maize LAI through remote sensing methods effectively, and then monitor the growth of maize, guide field production accurately, and improve the yield and quality of maize is one of the current research hotspots[3].

The main measurement methods of leaf area index are the direct measurement method and indirect measurement method[4]. The direct measurement method has shortcomings such as large labor intensity and a small acquisition range. So the direct measurement method is mainly used to collect data to train and verify the inversion model. The indirect measurement method is mainly carried out by satellite or UAV, using remote sensing data combined with measured data to invert the leaf area index[5,6]. Carcia-Matinez et al.[7] constructed a variety of vegetation indices through UAV multispectral data and performed vegetation coverage inversion. The results showed that the wide dynamic range vegetation index (WDRVI) was better to predict vegetation coverage. It has good sensitivity to the leaf area index. Xia et al.[8]

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constructed a linear regression model of leaf area index through hyperspectral data combined with field-measured data. The results showed that the green-red vegetation index (GRVI) affects vegetation changes. It is more sensitive, and the Normalized difference vegetation index (NDVI) can invert LAI well. Gao et al.[9] used UAVs to carry hyperspectral to invert the LAI of wheat in multiple stages and found the ratio type spectral index (RSI) is more sensitive to the leaf area index. Song et al.[10] constructed a Ratio vegetation index (RVI) and used univariate linear regression to perform LAI inversion on soybeans. The results showed that RVI and LAI have a good relationship between the power function and exponential function. Strachan et al.[11] found that the second moment of the near-infrared (near-infrared) index is correlated with leaf area positively by analyzing crop canopy reflectivity. They also pointed out that using the UAV hyperspectral data to invert the leaf area is feasible. Li et al.[12] analyzed the UAV visible light images of soybeans at three key growth stages. They constructed a variety of leaf area index inversion models. They also found that the full subset regression model has the best predictive effect.

Chen et al.[13] used many years of wheat growing degree days and canopy's NDVI to construct a winter wheat yield estimation index and to build a winter wheat yield inversion model effectively. Su et al.[14] took rice growing degree days as a parameter and used a logistic model, inverted the LAI and dry matter quality of rice effectively. Huang et al.[15] used the MODIS data and growing degree days of maize to construct the accumulated temperature-radiation model and the LAI integral area model to predict the maturity period of maize. The prediction of the LAI curve integral model R^2 reaches 0.87, and the prediction error is lower. It is not difficult to find that the predecessors used growing degree days for crop yield inversion or growth period estimation. They obtained good prediction results. It is indicating that growing degree days are an effective parameter for the construction of crop models. But the current research on the relationship between accumulated temperature and maize growth is lacking. Therefore, it needs to be studied urgently to explore the relationship between growing degree days and maize growth. And to improve the inversion accuracy of maize growth parameters.

Analysis of previous studies found that the current inversion of the leaf area index mainly uses spectral data to calculate different vegetation indexes, spectral derivatives, and other methods to construct regression models. As the crops grow and change, crop population structure, environment, and other performances will change, which affects the leaf area of crops. Therefore, only relying on spectral data and spectral-derived data to retrieve the leaf area index has certain shortcomings. This study comprehensively considers the crop structure and environmental changes during the process of crop growth. Exploring that regard the Canopy Height Model (CHM) of the plant, Growing degree days (GDD), and vegetation index as parameters, using the general linear regression model (GLR), multivariate nonlinear regression model (MNR), the partial least squares regression (PLSR) for multi-growth summer maize LAI inversion. And improving the inversion accuracy of summer maize LAI, providing data support for summer maize field fertilization and other management. Finally, it can help farmers to evaluate maize yield and quality.

2 Materials and methods

2.1 Overview of the study area

The study area with an altitude of about 27 m which is located in the Ecological Unmanned Farm of Shandong University of Technology (36°57′15″N, 118°12′50″E), Zhutai Town, Linzi District, Zibo City, Shandong Province. Its plains as the main terrain, belonging to a warm temperate zone semi-humid continental monsoon climate. The annual average temperature is about 13.2°C, the average rainfall is 650-800 mm, and the annual sunshine duration is about 2100 h. It is suitable for planting summer maize, wheat, and other crops. The total area of the experimental area in 2020 is 50 m×150 m, and five sample areas of 1 m×1 m were selected by the five-point sampling method for leaf area measurement and hyperspectral data collection. To improve the accuracy and generalization ability of the model, in 2021, Jinyangyang No. 6, Chunyu No. 985, and Nongxing No. 207 were used for multi-variety experiments. Three replicate experiments were set up for each variety, and five sample plots of 1m×1m were set up in each plot by equidistant sampling. The machine was used for two years to sow. The maize row spacing is 60 cm, and the plant spacing is 22.5 cm. Apply organic fertilizer and compound fertilizer as base fertilizer before sowing.

2.2 UAV multispectral data acquisition and processing

Using the DJI M210 equipped with Yusense MS600 multispectral camera (Yusense, Inc., Qingdao, China, Figure 1), the multispectral data were obtained from around July 20th (Twelve leaf stage), around August 9th (Tasseling stage), and around August 21st (Blister stage), 2020-2021. All the data were acquired from 10:00 a.m. to 12:00 a.m. on the same day. The weather was fine. During aerial photography, the drone had a flying height of 70 m, a flying speed of 4 m/s, a heading overlap of 80%, and a side overlap of 70%. The camera exposure mode was time exposure. The single-band channel and spectral resolution of the MS600 camera is 450 nm@35nm, 555 nm@25 nm, 660 nm@22.5 nm, 710 nm@10 nm, 840 nm@30 nm, and 940 nm@35 nm, and the pixel resolution is 1280×960. The storage format is ‘ .tif’. Two sets of standard whiteboard images are obtained before and after each data collection flight. The multispectral reflectance correction is performed on the data of each period through YusenseRef. The Pix4D mapper, a professional processing software for UAV aerial photograph data, was used to perform orthorectification and image stitching on the collected images. From it, a single band orthophoto with a ground resolution of 4.45 cm per pixel and digital surface model (DSM) images were obtained. Images of different growth

Figure 1 DJI M210and MS600 multispectral camera

stages were calibrated in space based on ground control points using ArcGIS.

2.3 Ground measurement data collection

During the growth of maize, the leaves show a three-layer distribution of upper, middle, and lower. The top new leaves are not fully extended and the leaf area is small. The middle leaves are fully extended and the leaf length is maximum, so it has the largest leaf area. The lower leaves are gradually senescent, so the leaf area is decreasing gradually. Therefore, to reflect the leaf area of the plant more accurately. The total number of leaves is stratified when the leaf area surface is measured, and select the representative leaves of each layer are as the measurement object. Yaxin1242 (Beijing Yaxin Liyi Technology Co., Ltd., China) leaf area meter can quickly measure crop leaf area, perimeter, and other parameters. it does not need to be calibrated before use. So it is convenient and quick. In this study, two representative samples were selected in the sample area to measure the leaf area. During the measurement, the total number of maize leaves was divided into three layers, the upper, middle, and lower layers. In each layer, we selected a typical leaf to measure the leaf area three times and took the average value as the final leaf area of this leaf. Recording the number of leaves in each layer, the GPS position of the plant, and the total number of plants in the sample point (Figure 2).

Figure 2 The measurement of the leaf area

The PSR1100-f hyperspectral (Spectral Evolution, USA) measuring instrument has a measurement range of 320-1100 nm and a sampling interval of 1.5 nm. The data can be stored as a .csv file directly. this measuring instrument was used to conduct a hyperspectral collection of maize at sampling points. The collection time is from 11:00 a.m. to 2:00 p.m. Before it, a standard whiteboard was used to calibrate and remove the influence of dark current. The probe is 0.5 m away from the crop canopy during collection. It is vertical on the ground. Each sample point was collected 5 times, and the average value was taken as the final spectral curve of that point.

Because maize plants in the bell mouth stage are relatively sparse. the vigorous maize plants were selected in the sample points to measure hyperspectral data three times. The average value was taken as the final spectral data of this sample point during the period. A total of 150 sets of data were collected in three growth stages (Table 1) over two years.

Table 1 Details of data collection for three growth stages

Year	Data type	Twelve leaf stage	Tasseling stage	Blister stage
2020	Plant height/bar	10	10	10
	Hyperspectral curve/bar	30	50	50
	Leaf area value/bar	90	90	90
	Final samples/sets	5	5	5
2021	Plant height/bar	90	90	90
	Hyperspectral curve/bar	270	450	450
	Leaf area value/bar	270	270	270
	Final samples/sets	45	45	45

2.4 Research methods

2.4.1 Calculation of measured leaf area

The leaf area index adopts the method of taking the average value per unit area. In the calculation, the average value of the leaf area (S_i, m^2) of each layer of the representative leaf is multiplied by the total number of leaves (N_i) in each layer, then accumulates the three-layer leaf surface of each plant. Multiply the leaf area value by the total number of plants at the sample point (n) and divide by 2. Finally, this value is divided by the plot area (S, m^2) to get the final leaf area index. The calculation formula is as follows:

$$\mathrm{LAI}_j = \frac{\sum_{i=1} (N_i \times S_i) \times n}{2 \times S} \quad (1)$$

where, LAI_j is the leaf area index of each plot; j is the number of plots (j =1, 2, 3, ...); i is the number of leaves (i =1, 2, 3, ...).

2.4.2 Calculation of growing degree days during growth stages

The growing degree days refer to the sum of the effective temperature during a growth stage. It is the difference between the daily temperature during the growth stage and the lower limit temperature of crop growth. Generally, it was considered that the lower limit temperature of maize grown in North China is 8°C-10°C[16-18], so in this study, the lower limit temperature was used as 10°C and the following calculation formula was used to calculate the accumulated temperature.

$$\mathrm{GDD}_i = \sum_{i=1}^{n} (T_i - T) \quad (2)$$

where, GDD_i represents the effective accumulated temperature at each stage, °C; T_i represents the daily average temperature during the growth stage, °C; T is the lower limit temperature of maize, °C; n is the number of growing days.

The daily temperature data of this study were obtained from the field weather station. It recorded the daily temperature and rainfall changes in the study area within a year. The cumulative effective accumulated temperature of summer maize during each growth stage was calculated by Equation (2) (Table 2).

Table 2 Growing degree days in each growth stage of summer maize (°C)

Classification	Twelve leaf Stage	Tasseling stage	Blister stage
2020	501.9	845.3	1060.4
2021	521.2	863.9	1148.7

2.4.3 Calculation of plant height and vegetation index

ArcGIS was used to perform the plant height calculation. First, 20 bare sites were selected from the UAV DSM images randomly. The height value was recorded and taking the average value as the final height of the bare area. Then, using ArcGIS's map algebra tool to convert the DSM data, subtract the height of the bare ground to obtain the CHM of the plant[19]. According to the GPS of the measured point, the 150 sets of CHM values were got from the DSM data. The measured plant height at the ground point and the

CHM obtained from the image were tested for accuracy, and according to the measured plant height value to correct CHM.

At present, many scholars have inverted the leaf area index based on the vegetation index. They found that the vegetation index constructed in the single red band has a weak correlation with LAI. But the vegetation index constructed on the multi-band red band has a strong correlation with LAI[20,21]. Nine plant vegetation indexes were constructed on the UAV multispectral data for LAI inversion. Such as WDRVI, Green Red Vegetation Index (GRVI), NDVI, RVI, Plant Biochemical Index (PBI), Enhance Vegetation Index (EVI), Optimized Soil-adjusted Vegetation Index (OSAVI), Modified Simple Ration Index (MSR), and Three gradient difference vegetation index (TGDVI)[22,23]. The calculation method of these vegetation indices is listed in Table 3.

2.4.4 Accuracy test of multispectral vegetation index

This research examines the accuracy of UAV multispectral data through correlation analysis of vegetation index. When acquiring PSR1100-f hyperspectral data, the GPS information of the acquisition point was also recorded. After calibration of the GPS point and multispectral image mark point, the spectral information of the corresponding position could be obtained from the multi-spectrum according to the position point. In this study, owing to the multispectral data obtained as the average reflectance of the band, the spectral band analysis could not be performed. Thus, the multispectral data were regarded as the center, using the corresponding range of the average of the hyperspectral. Correlation vegetation index construction was carried out on the spectral data of the two data. The correlation analysis of the vegetation index constructed by the two data was carried out to verify the accuracy of the multi-spectral data. To include as many bands as possible, this study selects four vegetation (PBI, NDVI, RVI, and EVI) which include R, G, B, and NIR channels for spectral accuracy testing.

Table 3 Vegetation index and calculation method

Vegetation index	Name	Equation
WDRVI	Wide dynamic range vegetation index	$(0.1R_{NIR}-R_{red})/(0.1R_{NIR}+R_{red})$
GRVI	Green red vegetation index	$(R_{green}-R_{red})/(R_{green}+R_{red})$
NDVI	Normalized difference vegetation index	$(R_{NIR}-R_{red})/(R_{NIR}+R_{red})$
RVI	Ratio vegetation index	R_{NIR}/R_{red}
PBI	Plant biochemical index	$\mathrm{R}_{NIR}/\mathrm{R}_{green}$
EVI	Enhance vegetation index	$2.5(R_{NIR}-R_{red})/(R_{NIR}-7.5R_{blue}+6R_{red}+1)$
OSAVI	Optimized soil-adjusted vegetation index	$1.16(R_{NIR}-R_{red})/(R_{NIR}+R_{red}+0.16)$
MSR	Modified simple ratio index	$(R_{NIR}-R_{blue})/(R_{red}-R_{blue})$
TGDVI	Three gradient difference vegetation index	$(R_{NIR}-R_{red})/(\lambda_{NIR}-\lambda_R)-(R_{red}-R_{green})/(\lambda_R-\lambda_G)$ λ is the length of band

2.4.5 Construction method and evaluation of summer maize leaf area inversion model

Linear and nonlinear regression models have the advantages of simple structure and good adaptability[24]. They are used in the construction of multivariate regression models widely. The PLS method is widely used in various fields because of its reliability in multivariate data processing. This method is based on principal component analysis and principal component regression. It has good adaptability to multi-linear correlation variables, and its regression model is mainly used to predict the target change[25]. This study used the GLR model, the MNR model, and the PLSR model to construct the inversion model.

In this study, the partial least square regression, and linear and non-linear regression were used to construct the LAI inversion model. The measured data were used to verify the accuracy of the model. The root means square error (RMSE) and coefficient of determination (R^2) were used to evaluate the accuracy of different models.

3 Results and discussion

3.1 Verification of plant height and multi-spectral vegetation index accuracy

The Spearman correlation coefficient can better reflect the correlation of discontinuous variables, and the data adaptability is good. Therefore, the Spearman correlation coefficient was used as the accuracy verification standard to verify the hyperspectral vegetation index and the ground sampling points in the three stages. The correlations of the UAV Multispectral Vegetation Index are listed in Table 4. A method similar to Reference [26] was used, analyzing the vegetation index constructed by the multispectral center band and the range of the hyperspectral center band. It was found that the Spearman correlation between the two was better than 0.64, and the significance P-value was less than 0.01. That means that the two were significantly correlated. It could be seen that the hyperspectral data and the multispectral (R, G, B, and NIR) data were related significantly. It was shown that the UAV multispectral data was reliable. Thus, the vegetation index construction and inversion model construction could be carried out through UAV multispectral data.

Table 4 Correlation test of vegetation index

Vegetation index	Correlation coefficient	*p*-value
PBI	0.716**	0.000
EVI	0.674**	0.000
RVI	0.718**	0.000
NDVI	0.641**	0.000

Note: **At the 0.01 level (two-tailed), the correlation is significant.

Analyzing the effective plant height (CHM value) obtained based on DSM and the measured plant height, it was found that the correlation between CHM value and measured plant height was 0.894. The significance p-value was less than 0.01 and significant correlation. The measured value was a linear model with CHM value R^2 reached 0.8149 (The red line in Figure 3), which was consistent with the results of Gao et al.[27] It could be known from Figure 3 that the points of the measured data were located above the 1:1 straight line (The black line in Figure 3). But they were evenly distributed on both sides of the linear fitting function. It indicates that there was a certain deviation between the measured value and the extracted value. The CHM value could not be used directly, and the linear fitting function was used to correct the CHM (The blue line in Figure 3), using the corrected CHM value instead of the measured plant height to build the model.

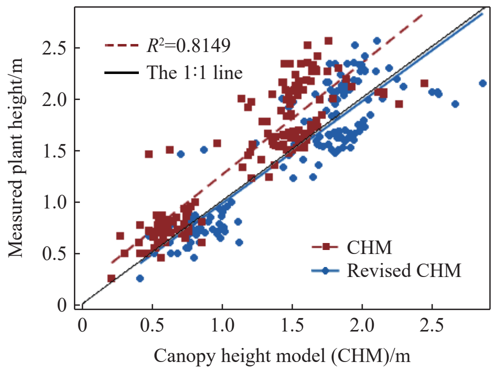


Figure 3 Verification results of plant height accuracy

3.2 Correlation analysis of inversion model parameters

The correlations of vegetation index, CHM, GDD, and measured LAI (Table 5) were analyzed. We found that except for EVI and MSR, the correlation was not significant, and the significance P values of other parameters were all less than 0.01. The correlations between WDRVI, NDVI, RVI, PBI, OSAVI, CHM, GDD, and LAI all exceed 0.7, which were significant correlations extremely. The WDRVI, RVI, PBI, GDD, CHM, and LAI had the highest significance, and their values were all over 0.74. It showed that the crop LAI had a stronger correlation between the canopy height model and the vegetation index, which was constructed on the red band and the near-infrared band. The MSR had the weakest correlation of LAI, with a value of 0.084. It is shown that the correlation between the vegetation index (based on the blue band) and the crop leaf area index is weaker. With the extension of maize leaves, the chlorophyll content and leaf area increase, the absorption of the red band is stronger than the blue band, and the reflection of the near-infrared band is stronger than the green band, so the vegetation index constructed including the red band and the near-infrared band presents high correlation. Therefore, in this study, the seven planting indices were selected as the input value of the LAI inversion model, with a correlation better than 0.7. And we divided the 150 sets of data into a training set and validation set according to 2:1. Finally, a stepwise regression method was used to construct the multiple growth stages of summer maize LAI. The GLR model, the MNR model, and the PLSR model were compared in this study.

Table 5 Correlation between model parameter and LAI

Vegetation index	Correlation coefficient	*p*-value
WDRVI	0.748**	0.000
GRVI	0.633**	0.000
NDVI	0.716**	0.000
RVI	0.763**	0.000
PBI	0.775**	0.000
EVI	0.089	0.276
OSAVI	0.716**	0.000
MSR	0.084	0.305
TGDVI	0.411**	0.000
CHM	0.822**	0.000
GDD	0.81**	0.000

Note: **At the 0.01 level (two-tailed), the correlation is significant.

3.3 LAI retrieval results and precision evaluation of multiple growth stages in maize

The vegetation indices, CHM and GDD were used to construct linear, multivariate nonlinear, and partial least squares models (Table 6). Through analyzing the model F value (α=0.05), it was found that each model had a significant relationship with the parameters. That means the model can explain the relationship between the input variable and the dependent variable self effectively. It was further analyzed and found that only the GLR model based on the 6-planted vegetative index retained WDRVI, PBI, and RVI. It was shown that the WDRVI, PBI, and RVI contribution rates of the parameters of the general linear regression model were relatively large. In the stepwise regression of the model, it eliminated the insignificant. The final training set model R^2 was 0.6129, the testing set model R^2 was 0.5785, and the RMSE was 1.4169. After introducing CHM into the model, the testing set model R^2 increased by about 8%, and the RMSE decreased by 0.14. The effective plant height reflects changes in maize leaf area to a certain extent. When introduced GDD into the model, the testing set model R^2 increases by about 7%, and the RMSE decreased by 0.12. The effective accumulated temperature also reflects changes in maize leaf area to a certain extent.

Table 6 LAI inversion model for multiple growth periods

Classification	Input value	Model	F value	Training R^2	Testing R^2	RMSE
General linear regression model(GLR)	X_1, X_3, X_4	LAI=$-1.23-1.40X_1+0.08X_3+0.608X_4$	F(3,101)80.02	0.6129	0.5785	1.4169
	$X_1, X_2, X_3, X_4, X_5, X_6$	LAI=$-15.30-13.42X_1+2007X_2+0.39X_3+0.178X_4-1720X_5+2.509X_6$	F(6,98)38.63	**0.7028**	**0.6582**	**1.2759**
	$X_1, X_2, X_3, X_4, X_5, X_7$	LAI=$-35.66-28.46X_1+117\ 131X_2+0.982X_3-0.511X_4-100\ 948X_5+0.007\ 671X_7$	F(6,98)100.27	0.8599	0.6477	1.2955
Partial least squares regression (PLSR) model	X_1, X_2, X_3, X_4, X_5	LAI=$-15.39-13.07X_1+0.37X_3+0.63X_4-10\ 153.7X_2+8765X_5$	F(5,99)48.47	0.6187	0.5718	1.4309
	$X_1, X_2, X_3, X_4, X_5, X_6, X_7$	LAI=$-33.737\ 39-27.221\ 33X_1+0.934\ 62X_3-0.665\ 69X_4+112\ 299.609\ 86X_2-96\ 785.555\ 53X_5+1.460\ 84X_6+0.006\ 95X_7$	F(7,97)108.04	**0.8863**	**0.7102**	**1.1755**
Multivariate nonlinear regression model(MNR)	X_1, X_2, X_3, X_4, X_5	LAI=$-34+54\ 458X_2-8.76X_3+0.503X_4-124.3X_1-46\ 924X_5-77.1X_2^2-0.2197X_3^2-106.1X_1^2+18.42X_3{\cdot}X_5$	*	0.8002	0.4162	1.6675
	X_1, X_3, X_4, X_5, X_6	LAI=$-3.20-0.987X_4+20.70X_1+115.90X_5-22.11X_3-1.72X_6-142.4X_5^2+0.796X_6^2+0.0899X_4{\cdot}X_3-11.99X_1{\cdot}X_3+26.16X_5{\cdot}X_3$	*	0.8253	0.5219	1.509
	X_3, X_4, X_6, X_7	LAI=$2.612-2.199X_4-0.005\ 26X_7+1.267X_3+0.53X_6+2.258X_6^2+0.005\ 54X_4{\cdot}X_7-2.217X_6{\cdot}X_4-0.002\ 149X_3{\cdot}X_7+0.625X_3{\cdot}X_6$	*	**0.9278**	**0.7297**	**1.1345**

Note: F(m, $n-m-1$) significance level α=0.05, where m is the number of independent variables, $n-m-1$ is the degree of freedom, and the critical value of F can be checked by the F-test table. X_1: WDRVI, X_2: NDVI, X_3: RVI, X_4: PBI, X_5: OSAVI, X_6: CHM, X_7: GDD.

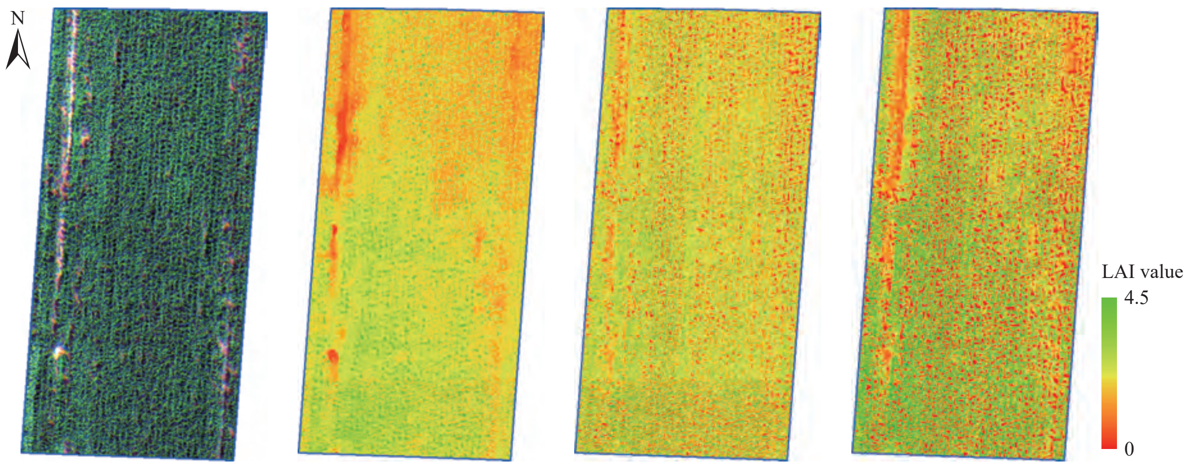
WDRVI, NDVI, RVI, PBI, and OSAVI were used to perform the PLS regression model, which highly correlated with LAI. The results show that the model has an R^2 of 0.6187 on the training set, while the testing set R^2 was lower than 0.6, and the RMSE was 1.4309. After the model introduced CHM and GDD, the R^2 of the PLS model on the training set and the testing set increased by 10%-27%, and the RMSE decreased by 0.3. That means the PLS model introduced the effective plant height and effective accumulated temperature can better predict changes in maize LAI.

Multivariate nonlinear regression was used to construct the LAI inversion model. On the training set, it was found that the R^2 of the multivariate nonlinear model based only on the vegetation index was 0.8002. However, on the testing set, the R^2 was only 0.4162, and the RMSE was 1.6775. That means the model was unstable. After introducing the CHM to the model. On the training set, the R^2 of this model has increased by about 2%. The R^2 on the testing set has increased by 9% and the RMSE has reduced by 0.16. On this basis, the model accuracy on the training set and testing set has improved by about 10%-20% after the introduction of GDD. Compared to the regression model that only contains the vegetation index. The R^2 of the model, which includes the GDD and CHM has an increase certainly. That means the effective accumulated temperature and the effective plant height have improved the inversion accuracy of the LAI model to a certain extent. Based on the above models found that the model inversion accuracy has differently improved by increasing the environmental parameters. This result is consistent with the research results of Liang et al[28].

To facilitate model expression, we used the X_1, X_2, X_3, X_4, X_5, X_6, and X_7 to replace WDRVI, NDVI, RVI, PBI, OSAVI, CHM, and GDD. After analyzing the model built by the three methods, it was found that the general linear regression model includes CHM has the best effect on the LAI inversion, and it recorded as LAI-1 (LAI=$-15.3-13.42X_1+2007X_2+0.39X_3+0.178X_4-1720X_5+2.509X_6$). The performance of the PLS model on the training set and the testing set was poor, which only the vegetation index. The RMSE of the model is improved, so the model is unstable. The PLS model that introduced GDD and CHM was better, and it recorded as LAI-2 (LAI=$-33.737\ 39-27.221\ 33X_1+0.934\ 62X_3-0.665\ 69X_4+112\ 299.609\ 86X_2-96\ 785.555\ 53X_5+1.460\ 84X_6+0.006\ 95X_7$). After the model introduced GDD and CHM in the multivariate nonlinear regression model, it has a higher R^2 in both the training set and the testing set, but the model's R^2 on the training set and the testing set was differently larger. Among the three multivariate nonlinear models has the best effect, which includes the GDD and CHM, and it recorded as LAI-3 (LAI=$2.612-2.199X_4-0.005\ 26X_7+1.267X_3+0.53X_6+2.258X_{6^2}+0.005\ 54X_4\cdot X_7-2.217X_6\cdot X_4-0.002\ 149X_3\cdot X_7+0.625X_3\cdot X_6$).

Among the three models, LAI-2 and LAI-3 both showed a better R^2 and RMSE on the training set and testing set, which were better than the LAI-1 model. The LAI-3 model had the highest R^2, which was 0.9827 and 0.7297. The R^2 of the LAI-2 model was 0.8863 and 0.7102. The difference between the two models of LAI-2 was smaller than that of the LAI-3 model, and the RMSE of the two models only differs by 0.04. Therefore, LAI-2 could be considered the optimal inversion model.

To verify the inversion effects of the LAI-1, LAI-2, and LAI-3 models, this study used three optimal models to perform LAI inversion for summer maize in three growth periods. The overall analysis found that the partial least squares regression model's inversion effect was the best. Comparing the actual inversion results (Figure 4 and Figure 5) during the grain construction period in the two years, we could see that in 2020, the LAI-2 complex inversion values were mostly around 6-8, and in 2021, they will be around 3-4, which is in line with the actual value of the year. The inversion effect of the LAI-1 and LAI-3 models was poor. LAI-1 was mostly lower than the true value, and LAI-3 was higher than the true value. Both two models have large inversion value errors. The comprehensive analysis found that the partial least squares regression model (LAI-2) includes WDRVI, NDVI, OSAVI, PBI, RVI, CHM, and GDD have the best inversion effect, with R^2 reaching 0.8863 and RMSE of 1.1755. Furthermore, we found that with the advancement of the maize growth periods, the LAI inversion value of each model showed a trend of first increasing and then slightly decreasing. Among them, the bell mouth period was the lowest, the tasseling period was the highest, and the grain completion period decreased slightly. The inversion effects of the LAI-2 model in each growth period were better than the former two so this model is suitable for summer maize LAI inversion in different periods.



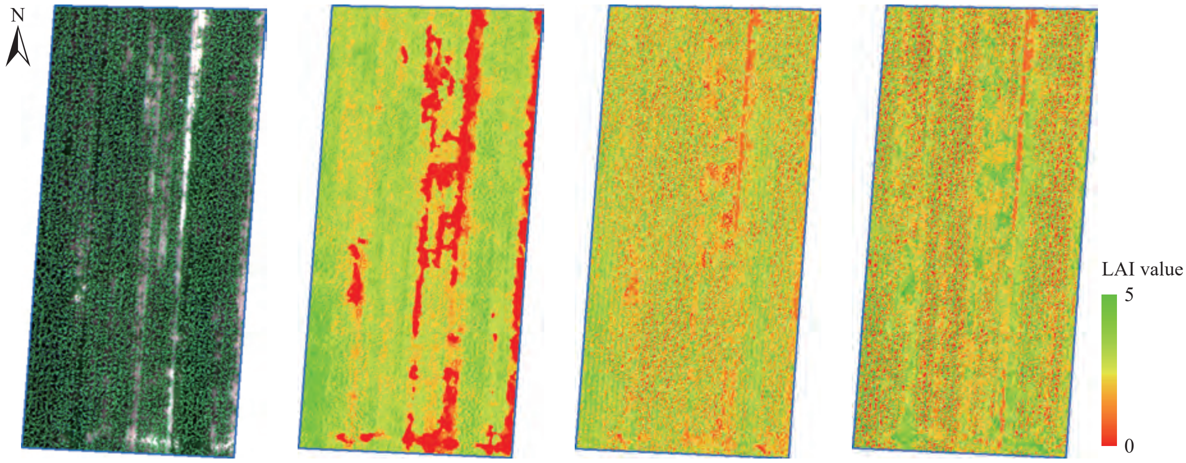
a. RGB b. LAI-1 c. LAI-2 d. LAI-3

Note: LAI-1 representative model: LAI=−15.30−13.42WDRVI+2007NDVI+0.39RVI+0.178PBI−1720OSAVI+2.509CHM; LAI-2 representative model: LAI=−33.737 39−27.221 33WDRVI+0.934 62RVI−0.665 69PBI+112 299.609 86NDVI−96 785.555 53OSAVI+1.460 84CHM+0.006 95GDD; LAI-3 representative model: LAI=2.612−2.199PBI−0.005 26GDD+1.267RVI+0.53CHM+2.258CHM² +0.005 54PBI·GDD−2.217CHM·PBI−0.002 149RVI·GDD+0.625RVI·CHM. Same below.

Figure 4 Inversion effect of the three models on August 9, 2020

3.4 Discussion

Spectral remote sensing is currently the mostly method for large-scale monitoring of crop leaf areas. Many scholars analyzed spectral data and spectral-derived data. They used statistical models, neural networks, and physical models to perform LAI inversion (Gao et al.[9]). However, the crop growth environment and plant



a. RGB b. LAI-1 c. LAI-2 d. LAI-3

Figure 5 Inversion effect of the three models on August 9, 2021

population structure will affect the change in crop leaf area. Therefore, this study considers the environmental accumulated temperature (growing degree days, GDD), plant effective height (canopy height model, CHM), and spectral data as the model inputs. We used the linear, nonlinear, and partial least squares regression methods to construct the LAI inversion model. The results show that the inversion effect of the model built by the GDD and CHM is better than the model based on spectral data alone. This result is consistent with Reference [29] result on wheat growth and meteorological factors. Through comparing this inversion model, we found that the nonlinear model including WDRVI, NDVI, OSAVI, RVI, PBI, CHM, and GDD performs the best. That means we can improve the inversion accuracy of the LAI model by introducing the environmental variables and plant structure parameters.

Raj et al.[30] found the linear model has the best inversion effect based on the UAV visible light image for leaf area index inversion. However, when we used the general linear regression model for LAI inversion in this study, the accuracy of this model is low. The reason is that the parameters have collinearity. The general linear regression model cannot solve the collinearity problem. Therefore, the partial least squares regression and multivariate nonlinear regression were used in this study to perform LAI inversion. By analyzing the inversion value and the real value of the optimal LAI inversion model constructed by the three methods. It was found that each model has a certain deviation. The reason is that this modeling only uses two years of data and the sample size is not large enough. The model may not be able to obtain higher accuracy. In addition, this research is based on the same region, and the adaptability of different regions needs to be tested.

The changes in maize LAI in this study are similar to the research[28]. Maize LAI increases with the growth stages slightly decreases[31]. By comparing the inversion effects of the three models, we found that the LAI-3 model for maize inversion in each period presents a higher LAI value, which does not conform to the actual situation of the LAI in the current periods. The analysis found that although the LAI-3 model reached a higher R^2 on the training set, the model R^2 on the testing set was only about 0.72, and the difference between the training set and the testing set R^2 is 20%. So the model is unstable, ultimately leading to higher LAI inversion values for maize in each period of LAI-3. Although the inversion model constructed in this study has achieved a certain inversion accuracy. It still has some problems. In the future, we will consider accumulating the effective accumulated temperature and the plant height data for many years. The convolutional neural networks or physical models are also considered to replace general linear regression methods to construct the LAI inversion model. To solve the problems of model collinearity, and insufficient data, and improve the accuracy of LAI inversion.

4 Conclusions

1) Ground hyperspectral data is significantly related to UAV multispectral data. That means the UAV multispectral data is accurate. So it is feasible to construct vegetation index and LAI inversion through UAV multispectral data.

2) This study shows that the three LAI inversion models have obtained better accuracy. The partial least squares regression model includes the RVI, WDRVI, NDVI, OSAVI, PBI, GDD and CHM has the best inversion effect. The training set model R^2 = 0.8863, the testing set model R^2=0.7102, and the RMSE=1.1755.

3) The study found that CHM and GDD effectively reflected the changes in crop population structure and growth period. The LAI inversion model was constructed by combining CHM, GDD, and vegetation index, which improved the accuracy of LAI inversion. It can provide a reference for field management such as maize growth monitoring and top dressing.

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