Inverting the Leaf Area Index of summer maize through the application of optimization methods

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Abstract: The leaf area index (LAI) of summer maize plays a pivotal role in estimating biomass, photosynthetic potential, transpiration, and various other crucial vegetation parameters. It serves as a vital indicator for evaluating growth progress and predicting crop yields. Unmanned Aerial Vehicle (UAV) remote sensing has proven to be a rapid and non-destructive tool for monitoring the LAI of summer maize. The objective of this study is to enhance the accuracy of the LAI inversion model for summer maize by leveraging different optimization algorithms. To achieve this, we designed varying fertilization levels to create distinct canopy structures. We employed a UAV multi-spectral remote sensing system to obtain 19 vegetation indices, which were collected concurrently with ground-based LAI measurements throughout the growing season. In our investigation, we applied multiple linear regression (MLR), Support Vector Machine Regression (SVR), and Random Forest Regression Model (RF) to establish regression models between the vegetation indices of summer maize and LAI over the entire growth period. For hyperparameter optimization of the SVR and RF models, we employed the Particle Swarm Optimization algorithm (PSO), Whale Optimization Algorithm (WOA), and Grey Wolf Optimization Algorithm (GWO) to search for optimal combinations of hyperparameters. The results demonstrated that Difference Vegetation Index (DVI), Green-Blue Ratio Index (GBRI), Standard Greenness Index (NGI), Wide Dynamic Range Vegetation Index (WDRVI), and Vegetation Infrared Ratio Index (SR) exhibited high correlations with LAI. Furthermore, the accuracy of LAI estimation models was significantly improved through the application of optimization methods. Notably, the LAI estimation model established using SVR-GWO yielded the highest accuracy (R^2=0.912, RMSE=0.607). In summary, the utilization of optimization algorithms has proven to be an effective approach in enhancing the precision of LAI estimation models, with promising applications in agricultural research and crop management.

Keywords: summer maize; multispectral remote sensing; leaf area index; vegetation index; inversion models; optimization methods
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1 Introduction

Presently, unmanned farming and precision agriculture are undergoing rapid development. The swift acquisition and analysis of crop information within farmlands serve as the fundamental prerequisite for the implementation of precision agricultural practices[1]. Enabled by an integrated agricultural information sensing system encompassing aerial, terrestrial, and celestial elements, a comprehensive three-dimensional data sensing and collection approach is achieved, thereby aggregating vital parameters essential for the construction of a repository of data for unmanned farming. This data repository forms the bedrock for informed decision-making grounded in scientific methodologies[2]. In the context of China, corn emerges as a prolific cereal crop, underlining the significance of conducting growth monitoring and leaf area index calculations, particularly in the case of summer corn cultivation. The Leaf Area Index (LAI) provides a quantitative depiction of the interplay between alterations in leaf blade dimensions and leaf density within crops. It stands as a pivotal indicator not only for crop photosynthesis and biomass but also as a significant agronomic parameter in the context of monitoring crop growth and yield[3]. Determining the LAI involves both direct and indirect measurement techniques[4-7]. Notably, the direct measurement method encompasses leaf collection and subsequent

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measurement of leaf area. Although straightforward in operation, this method entails a certain level of plant disruption, along with the requirement for manual leaf collection—resulting in a time-consuming and labor-intensive process. Furthermore, this method's reliance on manual sampling might not ensure a truly representative assessment.

Indirect measurement methods encompass spatial and ground-based detection techniques. Spatial detection leverages univariate or multivariate statistical regression models involving vegetation indices and LAI, established through the utilization of multispectral remote sensing data or hyperspectral data. Notably, a substantial body of research, both domestic and international, is dedicated to the utilization of satellite remote sensing technology[8-9]. Nonetheless, satellite remote sensing data exhibit limitations such as inadequate resolution, susceptibility to atmospheric influences and cloud cover, and feature obstructions, thereby posing challenges in meeting the demands of precision agriculture with regard to accuracy and flexibility.

In contrast, Unmanned Aerial Vehicle (UAV) remote sensing offers notable advantages including heightened resolution, diminished atmospheric interference, user-friendly and adaptable operations, as well as shortened data acquisition cycles[10-12]. This positions UAV remote sensing as an efficient, rapid, and precise means of acquiring data concerning crop growth areas. Li Qiang[13], and Shao Yajie[14] have demonstrated the utilization of UAV spectral information in the monitoring of crop growth.

To establish LAI inversion models, machine learning methods are frequently employed, with machine learning algorithms showcasing robust model fitting capabilities that are pivotal in remote sensing data inversion for LAI estimation. Notably, algorithms such as random forest and support vector machine hold significant advantages for nonlinear model fitting. Yang Nan[15], for instance, employed random forest, partial least squares regression, BP neural network, and support vector machine analysis to construct models for estimating both leaf area index and yield for wheat. Shao Guomin[16] similarly employed univariate linear regression, multivariate linear regression, and random forest regression to estimate LAI for summer maize across various irrigation conditions. Zhang Yaqian[17] developed an inversion model for maize leaf area index utilizing two algorithms—partial least squares and random forest regression. These algorithms were applied using LiDAR data, vegetation indices, and combined LiDAR and vegetation indices.

However, it's noteworthy that constructing random forest and support vector machine models entails the configuration of hyperparameters. These hyperparameters play a pivotal role in the accuracy of inversion model construction. Curiously, the aforementioned papers did not delve into the hyperparameter configuration during the inversion model construction. This omission could potentially result in models performing well on specific datasets but faltering to generalize effectively to different data scenarios.

To address the aforementioned limitations, this study focuses on summer maize cultivation within the Zibo Linzi ecological unmanned farm. The research endeavor involves gathering multispectral images spanning multiple growth stages, alongside corresponding ground truth data for Leaf Area Index (LAI) from the same periods. The overarching goal is to establish an accurate unmanned remote sensing model for LAI inversion in summer maize, thereby enabling precise predictions of its LAI. Three distinct algorithms—multivariate linear regression, support vector machine, and random forest—are employed to create the maize leaf area index inversion model. In parallel, to optimize the model's hyperparameters, this study introduces the particle swarm optimization algorithm[18], the gray wolf optimization algorithm[19], and the whale optimization algorithm[20-21] to fine-tune the support vector machine and random forest models. This comprehensive approach contributes to enhancing the accuracy and robustness of the LAI inversion model throughout the entire life cycle of maize vegetation. By meticulously evaluating the performance of the LAI inversion model under various optimization algorithms, this research establishes a summer maize inversion model characterized by its ability to generalize effectively. This holistic methodology bridges the existing gaps, ensuring a more accurate and adaptable model for predicting LAI in the context of summer maize cultivation.

2 Materials and Methods

2.1 Study Area and Experimental Design

The data collection for this experiment was conducted at the Ecological Unmanned Farm of the Shandong University of Technology, situated in the Linzi District of Zibo City, within Shandong Province, China (coordinates: 118.214° E, 36.954° N). The regional climate is characterized as a temperate monsoon climate, with an average annual precipitation of 650 millimeters. The mean annual temperature ranges from 12.5°C to 14.2°C, and the average annual sunshine duration spans from 2209.3 to 2523.0 hours. The frost-free period typically extends for 190 to 210 days annually. The experimental site is characterized by a loamy soil profile.

The present experiment was conducted within an ecological unmanned farm, focusing on a near-square corn plot measuring approximately 43×43 meters, as depicted in Figure 1. The chosen maize variety was Chunyu958, cultivated with a plant spacing of 26 cm and a row spacing of 60 cm. Sowing took place at a depth of 5 cm on June 21, 2022. Harvesting occurred on October 5 of the same year, spanning a full lifecycle of 106 days. To accentuate variations in corn growth across the experimental area, four distinct field management methods were established.

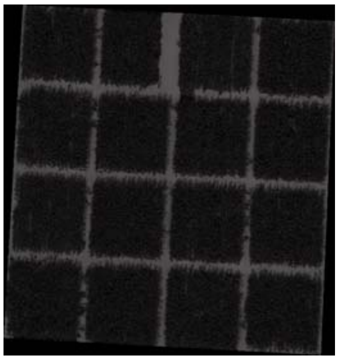


Figure 1 Distribution of Study Area

Compound fertilizer (26-6-8) served as the base fertilizer, while second application fertilization employed urea. On July 26, 2022, supplementary fertilizer was applied. The experimental groups were stratified into four levels, distinguished by the quantity of fertilizer administered: CK (no fertilizer), TR1 (30 kg base fertilizer), TR2 (30 kg base fertilizer and 20 kg follow-up fertilizer), and TR3 (40 kg base fertilizer and 20 kg follow-up fertilizer). The application of fertilizers adhered to the specifications outlined in Table 1. Each fertilization treatment consisted of four replicates, amounting to a total of 16 experimental plots, each measuring 10×10 meters and maintaining a 1-meter separation between adjacent plots.

Table 1 Test plot treatments

Treatment	base fertilizer (26-6-8) /kg·hm^{-2}	Second application (urea) /kg·hm^{-2}
CK	0	0
TR1	450	0
TR2	450	300
TR3	600	300

2.2 Data Acquisition and Preprocessing

To mitigate the impact of weather conditions on remote sensing images, UAV data acquisition for remote sensing was meticulously scheduled during clear and calm weather conditions. Additionally, for a comprehensive record of the maize growth cycle, data collection was strategically set on July 22nd, August 17th, and September 12th, 2022. UAV remote sensing data was procured between 11:00 AM and 2:00 PM Beijing time, while ground data collection occurred between 8:00 AM and 4:00 PM Beijing time.

The multispectral camera employed in this study is the Changguang Yuchen MS600 PRO, a six-channel multispectral camera boasting a pixel resolution of 1280×960. This camera encompasses six spectral bands, specifically at 450 nm, 555 nm, 660 nm, 710 nm, 840 nm, and 940 nm. The camera was affixed to the DJI M210 drone, which conducted flights at an altitude of 30 meters, maintaining a steady pace of 2 m/s. During flight operations, a lateral overlap rate of 70% was adhered to, and an overlap rate of 80% was maintained in the heading direction.

Images of the radiation calibration plate were captured both prior to takeoff and after landing. This plate was positioned on the ground. The drone was positioned approximately 80-100 cm above the ground, with its lens oriented vertically downward. It was of paramount importance that no shadows fell upon the calibration plate. These images were acquired to facilitate subsequent radiometric calibration, a critical step in the process. The Changguang Yuchen Yusense Ref software was employed to carry out this calibration.

The stitching process of multispectral remote sensing images was executed utilizing Pix4D. For geographic alignment, ArcGIS software was employed, and mask files were generated using ENVI software. The ENVI software was used to extract canopy spectral reflectance from each measurement plot in the multispectral image. This commenced with the establishment of the region of interest for each measurement plot, followed by the acquisition of multispectral reflectance through statistical analysis. The extraction of vegetation indices from the remote sensing image was accomplished by employing band operations within the ENVI software.

The primary focus of ground data collection revolves around the leaf area index (LAI) of summer maize. For each plot, three measurement plots measuring 1×1 m were randomly designated. Within each of these measurement plots, two maize plants were chosen at random for assessment. The yaxin1242 leaf area meter was employed to determine leaf area, offering the advantages of rapid measurement, user-friendliness, and eliminating the need for calibration. In practice, the leaf area meter was positioned on the chosen corn leaf, and upon hearing the dropping sound, the measurement process was initiated. The device was then systematically moved from the base of the leaf to its top while maintaining uniform motion. After releasing the button, the recorded data was read. This process was repeated three times for each leaf, ensuring robust and consistent measurements.

2.3 Vegetation Index Selection

The underlying principle of vegetation indices lies in the characteristic behavior of green vegetation or crops, which exhibit pronounced absorption in the visible red and blue light bands and substantial reflection in the near-infrared and green bands. The formulation of vegetation indices serves as a quantitative representation of vegetation growth. In this research, a compilation of 19 distinct vegetation indices, drawn from prior studies, was selected and computed. The detailed indices along with their corresponding calculation formulas are outlined in Table 2.

Table 2 Vegetation indices

Vegetation indices	Formula
NDVI	$NDVI = (R_{nir} - R_{red}) / (R_{nir} + R_{red})$
SR	$SR = R_{nir} / R_{red}$
EVI	$EVI = 2.5(R_{nir} - R_{red}) / (R_{nir} + 6R_{red} - 7.5R_{blue} + 1)$
DVI	$DVI = R_{nir} - R_{red}$
NLI	$NLI = (R_{nir} * R_{nir} - R_{red}) / (R_{nir} * R_{nir} + R_{red})$
OSAVI	$OSAVI = (1 + 0.16)(R_{nir} - R_{red}) / (R_{nir} + R_{red} + 0.16)$
MNLI	$MNLI = 1.5(R_{nir} * R_{nir} - R_{red}) / (R_{nir} * R_{nir} + R_{red} + 0.5)$
WDRVI	$WNRVI = (aR_{nir} - R_{red}) / (aR_{nir} + R_{red})\ \ (a = 0.12)$
MDD	$MDD = (R_{nir} - R_{red\ edge}) / (R_{red\ edge} - R_{green})$
INT	$INT = (R_{green} + R_{red} + R_{blue}) / 3$
SIPI	$SIPI = (R_{nir} - R_{blue}) / (R_{nir} + R_{red})$
NGI	$NGI = R_{green} / (R_{nir} + R_{green} + R_{red\ edge})$
NGI-RGB	$NGI - RGB = R_{green} / (R_{nir} + R_{green} + R_{red\ edge})$
NBI	$NBI = R_{blue} / (R_{red} + R_{green} + R_{blue})$
RBDI	$RBDI = R_{red} - R_{blue}$
GRDI	$GRDI = R_{green} - R_{red}$
RBRI	$RBRI = R_{red} - R_{blue}$
GBRI	$GBRI = R_{green} - R_{blue}$
VDVI	$VDVI = (2R_{green} - R_{red} - R_{blue}) / (2R_{green} + R_{red} + R_{blue})$

2.4 Model Accuracy Validation

For this study, a random sampling approach was employed, wherein 80% of the total samples (96) were chosen from the dataset encompassing three pivotal fertility periods. These samples were utilized for constructing the model, while the remaining 20% (24) were reserved for validating the model's performance. The efficacy of both modeling and validation was assessed through the utilization of two metrics: the coefficient of determination (R^2) and the root mean square error (RMSE). R^2 serves as a measure to assess the goodness of fit between the model’s predicted values and the actual values. It yields a value within the range of 0 to 1. In simple terms, a higher R^2 value indicates a superior alignment between the regression model and the data, underlining a stronger fit. Conversely, RMSE encapsulates the average error between the predicted and actual values of the model. This non-negative metric indicates the predictive accuracy of the model. Smaller RMSE values signify a higher predictive prowess of the model, as the discrepancies between the predicted and actual values are reduced. Conversely, larger RMSE values suggest a diminished predictive capacity, pointing towards increased disparities between the model's predictions and the actual outcomes.

3 Results

3.1 Relationship Between LAI and Vegetation Indices

The vegetation indices from the three distinct maize fertility test plots underwent Pearson correlation analysis with the Leaf Area Index (LAI). The Pearson correlation analysis, which gauges the strength and direction of linear correlation between two continuous variables, yields values spanning from –1 to 1. In this context, a value of -1 signifies a complete negative correlation, 1 indicates an absolute positive correlation, and 0 denotes no linear correlation. The outcomes of this analysis are graphically presented in Figure 2.

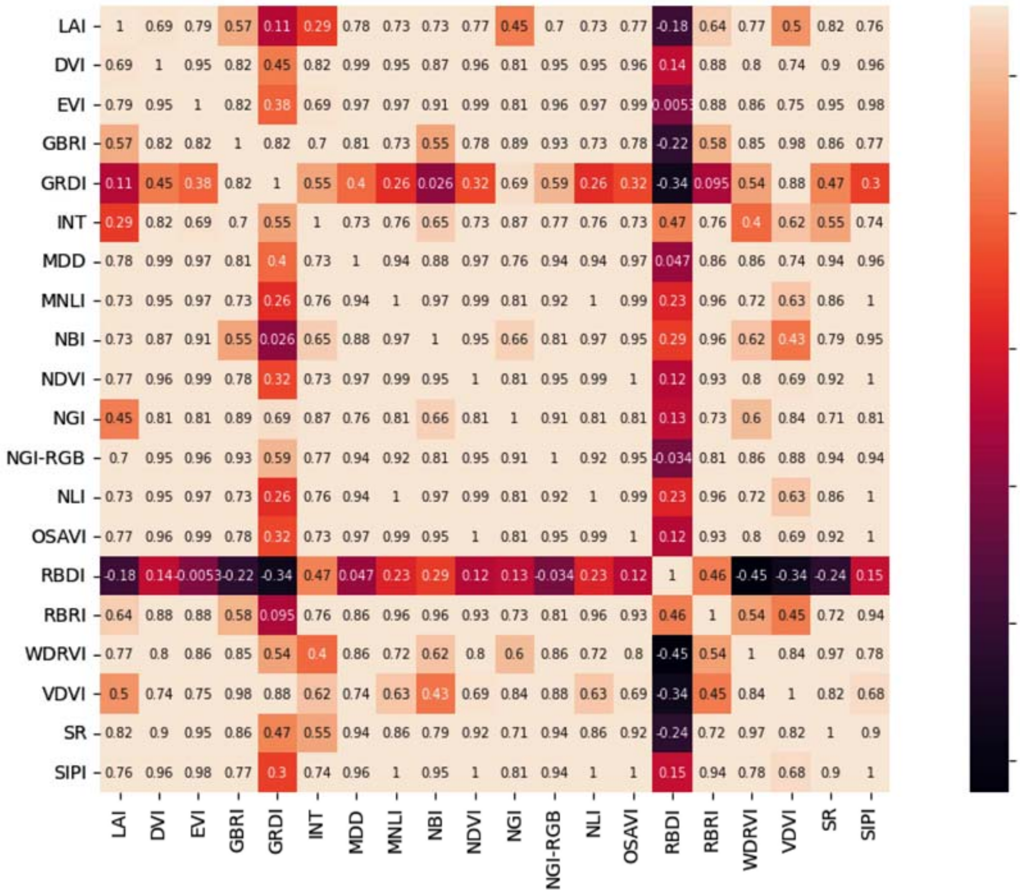


Figure 2 Heat map of correlation between vegetation index and LAI

Simultaneously, a correlation analysis was conducted among vegetation indices, where certain vegetation indices exhibited high collinearity. To reduce model complexity and mitigate the risk of overfitting, the vegetation indices were subjected to dimensionality reduction. Through this process, six vegetation indices were derived: Difference Vegetation Index (DVI), Green-Blue Ratio Index (GBRI), Normalized Greenness Index (NGI), Wide Dynamic Range Vegetation Index (WDRVI), Vegetation Red-Edge Ratio Index (SR), and Intensity Index (INT). Furthermore, due to the minimal correlation coefficient of 0.267 between INT and LAI, the correlation between these two variables was noted to be low.

Based on correlation analyses conducted between vegetation indices and Leaf Area Index (LAI), as well as among vegetation indices themselves, the selection of input variables included DVI, GBRI, NGI, WDRVI, and SR. Simultaneously, LAI was identified as the designated output variable. Subsequently, the maize LAI inversion model was formulated employing three distinct algorithms: Multiple Linear Regression (MLR), Random Forest (RF), and Support Vector Regression (SVR). Furthermore, particle swarm optimization, grey wolf optimization, and whale optimization algorithms were applied to fine-tune hyperparameters for the Random Forest and Support Vector Machine machine learning algorithms.

The measured Leaf Area Index (LAI) of maize under various fertilization treatments during the critical fertility period is depicted in Figure 3. The LAI exhibited a pattern of increase followed by decrease, reaching its peak value in the middle phase of maize growth. The maximum LAI values for the four treatments were recorded as 5.29, 6.09, 6.479, and 6.65, respectively. Notably, the control treatment (CK), which received no fertilization, yielded a lower LAI compared to the three other fertilization treatments. In the initial stage of corn growth, LAI values for TR1, TR2, and TR3 were relatively similar.

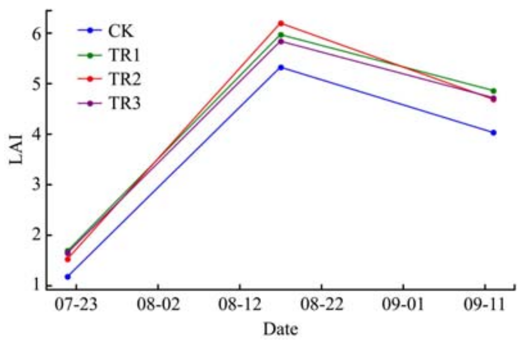
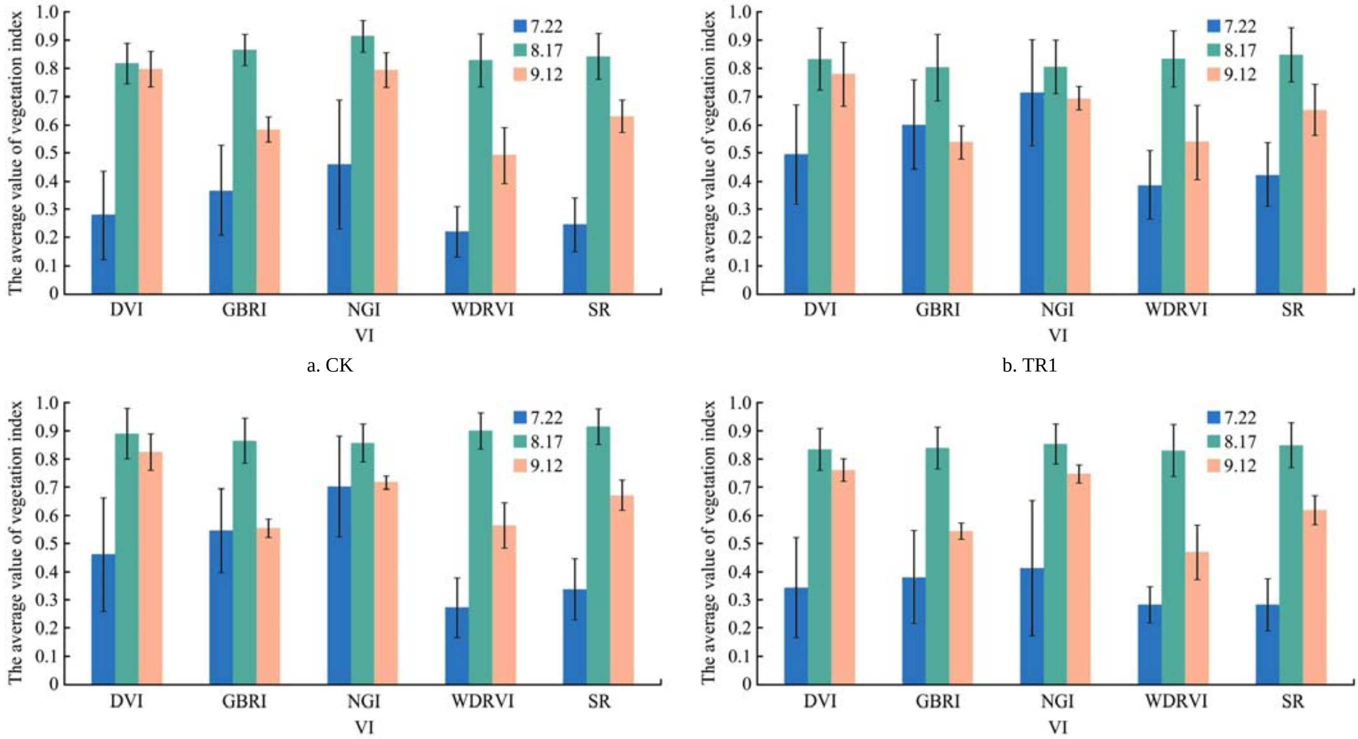


Figure 3 LAI under different fertilizer treatments at key fertility stages

Following the application of fertilizer on July 26, the LAI of TR2 and TR3 gradually surpassed that of TR1. As the corn plants entered the late growth phase, their leaves underwent senescence and withering, leading to a gradual reduction in LAI across all treatments. Figure 4 displays the mean vegetation index, calculated according to the formula detailed in Table 2. The figure clearly illustrates a consistent trend in the vegetation index when compared to the leaf area index. During the initial growth stages to the middle growth stages, each vegetation index exhibits a discernible upward trajectory. However, in the late growth stage, the vegetation index aligns closely with the leaf area index, gradually declining.



a. CK b. TR1

c. TR2 d. TR3

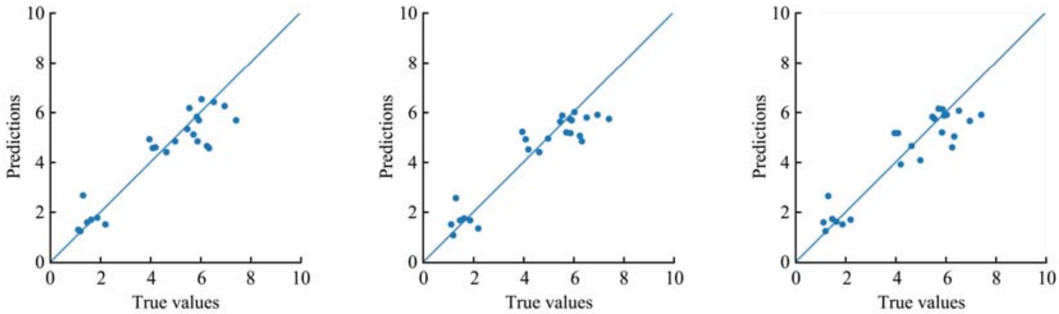
Figure 4 Mean values of vegetation index under different fertilization treatments

3.2 Evaluation of LAI Inversion Model Precision

Out of the total 120 test samples, a set of 96 samples was randomly designated for training purposes, while the remaining 24 samples were reserved as the test set. The MLR, RF, and SVR algorithmic models were leveraged to undertake the inversion of the Leaf Area Index (LAI) for summer maize. The accuracy outcomes yielded by each model are succinctly presented in Table 3. Among the three algorithmic models, the Random Forest regression model demonstrated superior accuracy ((R^2=0.865, *RMSE*=0.75), outperforming the other two regression models. In comparison to both Multiple Linear Regression and Support Vector Machine models, the Random Forest model showcased (R^2 values elevated by 0.016 and 0.005, accompanied by lower *RMS* values reduced by 0.041 and 0.013, respectively. Figure 5 graphically illustrates the predicted LAI samples generated by distinct regression models, juxtaposed with the actual measured samples. Notably, the RF regression model exhibits a notably higher concentration of samples aligned around the *Y*=*X* curve, underscoring its enhanced predictive precision.

Table 3 Maize LAI and vegetation index of different estimation models

Regression model	R^2	*RMSE*
MLR	0.849	0.791
SVR	0.86	0.763
RF	0.865	0.750



a. MLR b. SVR c. RF

Figure 5 Maize LAI prediction model with different estimation model

3.3 Model Precision Evaluation with Optimization Techniques

Employing the Particle Swarm Optimization Algorithm, Whale Optimization Algorithm, and Grey Wolf Optimization Algorithm, the Support Vector Regression (SVR) and Random Forest (RF) algorithmic models were further optimized to reestablish the Leaf Area Index (LAI) inversion model for summer maize encompassing the entire reproductive period.

In comparison to using the SVR algorithm in isolation, the inclusion of the three optimization algorithms individually has led to varying degrees of enhancement in prediction accuracy. Illustrated in Table 4, the R^2 values for the test set now stand at 0.905, 0.894, and 0.912, respectively, all of which surpass the performance achieved by the unoptimized SVR algorithm (0.86). Correspondingly, the *RMSE* alues are now 0.629, 0.665, and 0.607, respectively, signifying a reduction from the *RMSE* of the unoptimized algorithm (0.763).

Among the three optimization algorithms, the Gray Wolf Optimization Algorithm yields the highest model accuracy for the SVR algorithm. It boasts an R^2 value that surpasses those obtained using the Particle Swarm Optimization (PSO) and Whale Optimization Algorithm (WOA) by 0.006 and 0.018, respectively. Additionally, its RMSE value is lower by 0.022 and 0.058 when compared to the SVR algorithm utilizing the PSO and WOA optimization algorithms. Figure 6 visually represents the augmented accuracy of the SVR inversion model after the integration of optimization algorithms.

Table 4 Maize LAI and vegetation index of the SVR model after incorporating the optimization approach

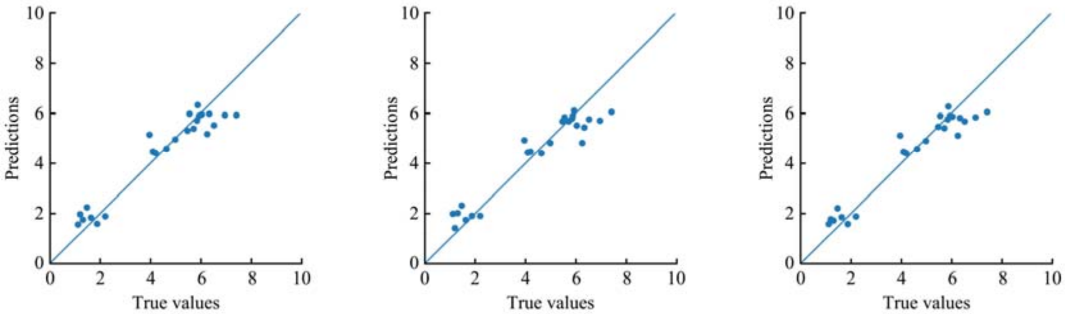
Regression model	R^2	*RMSE*
SVR+PSO	0.905	0.629
SVR+WOA	0.894	0.665
SVR+GWO	0.912	0.607

Compared with the RF algorithm alone, the prediction accuracies of the optimized RF algorithm with the addition of the three optimization algorithms separately are all improved to different degrees. As outlined in Table 5, the R^2 values for the test set now read 0.897, 0.872, and 0.902, all of which surpass the R^2 value achieved by the unoptimized RF algorithm (0.865). Correspondingly, the *RMSE* values have now diminished to 0.653, 0.73, and 0.622, respectively, showcasing a reduction from the *RMSE* of the unoptimized algorithm (0.75).

Table 5 Maize LAI and vegetation index of RF model after incorporating the optimization approach

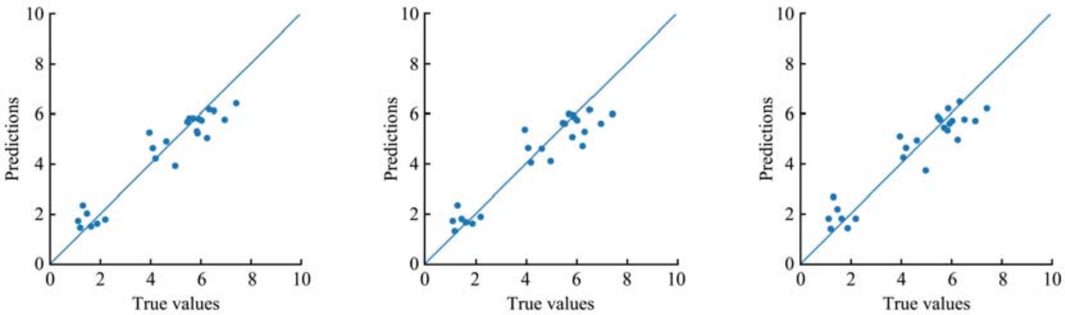
Regression model	R^2	*RMSE*
RF+PSO	0.897	0.653
RF+WOA	0.872	0.73
RF+GWO	0.902	0.722

Among these optimization algorithms, the Gray Wolf Optimization Algorithm has yielded the highest model accuracy for the RF algorithm. Its R^2 value outperforms those obtained using the Particle Swarm Optimization (PSO) and Whale Optimization Algorithm (WOA) by 0.005 and 0.03, respectively. Similarly, the *RMSE* is lower by 0.03 and 0.108 when contrasted with the RF algorithm utilizing the PSO and WOA optimization algorithms. Figure 8 visually illustrates the improved accuracy of the RF inversion model after the incorporation of optimization algorithms.



a. SVR+PSO b. SVR+WOA c. SVR+GWO

Figure 6 SVR model corn LAI prediction model after adding the optimization method



a. RF+PSO b. RF+WOA c. RF+GWO

Figure 7 RF model corn LAI prediction model after adding the optimization method

It is noteworthy that the predictive precision of both the Support Vector Regression (SVR) and Random Forest (RF) algorithm models was consistently elevated when employing the Grey Wolf Optimization Algorithm, surpassing the alternative optimization methodologies.

4 Discussion

The utilization of vegetation indices for maize LAI inversion is a widely employed technique in crop monitoring. These indices are predominantly composed of differences and ratios, effectively mitigating errors present in individual bands[22]. Previous research[23] has indicated that the Standardized Ratio (SR) exhibits a robust fitting accuracy to LAI, while the red-edge band demonstrates heightened sensitivity in tracking healthy vegetation growth. Additionally, another study[24] revealed that the WDRVI displays substantial sensitivity to LAI, with the red-edge band showcasing consistent performance across different crop species and demonstrating limited sensitivity to soil background.

In alignment with these findings, the present study yielded similar outcomes upon assessing the correlation between vegetation indices and LAI. Notably, vegetation indices such as DVI, EVI, NDVI, SAVI, GBRI, NGI, WDRVI, VI, and SR exhibited noteworthy correlations with the Maize LAI. This observation underscores the capability of these extracted vegetation indices to effectively reflect the growth status of the crop. These vegetation indices were derived through operations on the red band, near-red band, and red-edge band, revealing a significant correlation between the maize leaf area index and these spectral bands. Moreover, strong correlations were observed among different vegetation indices.

Through a comprehensive comparison of the inversion accuracies achieved by Multiple Linear Regression (MLR), Random Forest (RF), and Support Vector Machine (SVM) regression models across the entire life cycle of the maize LAI model, the study determined that all three algorithms demonstrated commendable performance, each achieving R^2 values surpassing 0.849. Notably, the RF algorithm exhibited superior performance. Similarly, in the work of SHAO Guomin[16], the effectiveness of Random Forest (RF) was also observed in the construction of maize Leaf Area Index (LAI) inversion models using both Multiple Linear Regression and Random Forest regression methods. Corroborating this, Leng Xin[25] found that the accuracy of the hyena algorithm neural network surpassed that of the BP neural network when inverting the woodland leaf area index. This highlighted the potential for enhancing neural network model accuracy through the integration of the hyena algorithm. Similarly, Zhang Jin[26] enhanced LAI estimation model prediction accuracy by utilizing support vector machine and BP neural network models, optimized using the particle swarm algorithm.

Comparative analysis with the existing literature[26] demonstrates the novel contributions of this study in terms of optimizing machine learning algorithms for maize LAI estimation. Specifically, we have introduced two innovative optimization methods, the Grey Wolf Optimization Algorithm and the Whale Optimization Algorithm, to fine-tune the hyperparameters of Random Forest (RF) and Support Vector Machine (SVM) models. Our results emphasize the superior performance of the Grey Wolf Optimization Algorithm in terms of speed and accuracy when optimizing RF and SVM models, outperforming the traditional Particle Swarm Optimization Algorithm.

The enhanced accuracy achieved by the RF and SVM models utilizing the Whale Optimization Algorithm is less pronounced. This can be attributed to the algorithm's relatively slower convergence rate and limited exploratory capabilities, leading to a higher likelihood of converging towards local optima. In contrast, although the Particle Swarm Optimization Algorithm enhances accuracy, it suffers from slower convergence speeds and increased computational time, thus falling short when compared to the Grey Wolf Optimization Algorithm.

It is evident that RF and SVM models, when optimized using the Grey Wolf Optimization Algorithm, consistently exhibit higher accuracy. This success can be attributed to the algorithm's enhanced diversity and rapid convergence, facilitating the identification of optimal parameter combinations. The application of optimization algorithms to automate the search for superior hyperparameters within regression models significantly elevates the accuracy of our inversion model. This, in turn, greatly enhances the precision of Support Vector Regression (SVR) and Random Forest (RF) in maize LAI estimation, which is of utmost importance in the context of agricultural research and applications.

5 Conclusions

Conducting a correlation analysis on several vegetation indices in relation to the Leaf Area Index (LAI) of maize, it was revealed that indices such as DVI, EVI, NDVI, SAVI, VI, and SR exhibited a robust correlation with LAI. These vegetation indices exhibited a correlation primarily with the red and near-infrared bands. Consequently, it can be inferred that vegetation indices associated with these bands displayed pronounced correlations with LAI, with correlation coefficients reaching values as high as 0.78. Additionally, a strong correlation was also observed among various vegetation indices.

In the process of performing regression modeling for Leaf Area Index (LAI) and vegetation indices, it was evident that the RF regression model showcased superior accuracy in estimating LAI. Upon the inclusion of the optimization algorithm, each regression model witnessed varying degrees of accuracy improvement. When contrasting the Particle Swarm Optimization Algorithm and the Whale Optimization Algorithm, the Gray Wolf Optimization Algorithm emerged as the frontrunner, yielding heightened LAI estimation accuracies for both RF and SVM regression models, attaining R^2 values of 0.902 and 0.912. Notably, SVR-GWO achieved the highest estimation accuracies. The incorporation of optimization algorithms distinctly enhances the accuracy of maize LAI inversion. Furthermore, the automatic optimization of hyperparameters contributes to augmenting the model's generalization capacity.

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