

Article

Estimating Rice SPAD Values via Multi-Sensor Data Fusion of Multispectral and RGB Cameras Using Machine Learning with a Phenotyping Robot

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Abstract

Chlorophyll is crucial for crop photosynthesis and useful for monitoring crop growth and predicting yield. Its content can be indicated by SPAD meter readings. However, SPAD-based monitoring of rice is time- and labor-intensive, whereas remote sensing offers non-destructive, rapid, real-time solutions. Compared with mainstream unmanned aerial vehicle, emerging phenotyping robots can carry multiple sensors and acquire higher-resolution data. Nevertheless, the feasibility of estimating rice SPAD using multi-sensor data obtained by phenotyping robots remains unknown, and whether the integration of machine learning algorithms can improve the accuracy of rice SPAD monitoring also requires investigation. This study utilizes phenotyping robots to acquire multispectral and RGB images of rice across multiple growth stages, while simultaneously collecting SPAD values. Subsequently, four machine learning algorithms—random forest, partial least squares regression, extreme gradient boosting, and boosted regression trees—are employed to construct SPAD monitoring models with different features. The random forest model combining vegetation indices, color indices, and texture features achieved the highest accuracy ($R^2 = 0.83$, $RMSE = 1.593$). In summary, integrating phenotyping robot-derived multi-sensor data with machine learning enables high-precision, efficient, and non-destructive rice SPAD estimation, providing technical and theoretical support for rice phenotyping and precision cultivation.

Keywords: phenotyping robot; multispectral image; RGB image; machine learning; multi-sensor fusion



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1. Introduction

As one of the most important food crops, rice plays a crucial role in addressing food security challenges [1]. The content of chlorophyll is an important indicator for photosynthesis, exerting a substantial impact on rice yield and growth status [2]. The real-time, non-destructive, and high-precision monitoring of rice SPAD is of great significance. Traditional measurement methods can accurately determine chlorophyll content but are destructive, cumbersome, and incapable of providing real-time monitoring. In practical production, leaf

SPAD values are commonly used to characterize plant chlorophyll [3,4]. Consequently, non-destructive, real-time, and high-throughput monitoring of rice SPAD values holds important implications for rice breeding phenotyping and precision cultivation management.

The Internet of Robotic Things (IoRT) integrates robotics with Internet of Things (IoT) technologies to enable seamless data collection, processing, and exchange. Characterized by enhanced intelligence, mobility, and autonomy, IoRT holds great potential in precision agriculture [5]. Phenotyping monitoring robot systems are also recognized as crucial platforms for high-throughput plant phenotyping [6]. Commonly used unmanned aerial vehicle (UAV) platforms are typically equipped with a single type of sensor, such as spectral cameras, RGB cameras, thermal imagers, and LiDAR. The information obtained by a single sensor is limited, which, to some extent, affects the accuracy of remote sensing monitoring. Currently, some spectral cameras are integrated with RGB cameras, but the imaging quality of the miniature industrial camera modules used is not comparable to that of professional RGB cameras, thus compromising the information contained in the captured color images. In contrast, phenotyping robots can be equipped with multiple sensors and are capable of acquiring phenotypic parameters at the population, individual plant, and organ levels with high precision and high throughput in large-scale fields. Compared with other phenotyping monitoring platforms, such as satellites and UAVs, they exhibit the most balanced overall performance [7].

UGV-based phenotyping systems have been increasingly applied in agricultural scenarios, which can navigate through complex field environments to capture high-resolution imagery of crop canopies and monitor dynamic changes in plant growth over time. Fan et al. utilized an ultra-narrow wheeled robot equipped with an RGB-D camera, which could identify stalks using a convolutional neural network and effectively measure stalk diameter based on point clouds in maize rows [8]. The self-propelled phenotyping robot platform in reference [9], with a 2D LiDAR and a low-cost spectral reflectance sensor, achieved extremely high correlation between the acquired canopy height and manual measurements, and the spectral indices (NDVI and PRI) showed good consistency with results from expensive spectrometers. Thus, phenotyping robots equipped with multiple sensors demonstrate substantial application potential for the high-throughput and high-precision monitoring of rice SPAD.

Crop canopy chlorophyll significantly affects the reflectance of vegetation spectra, which enables the quantitative analysis of chlorophyll content using spectral information. SPAD values are measured manually by clamping leaves with a SPAD meter, which are used to characterize the chlorophyll content of leaves [10,11]. Ma et al. developed SPAD prediction models for maize under different irrigation levels in Inner Mongolia using plant height, leaf area index, and vegetation indices derived from UAV multispectral images [12]. Xie et al. employed UAV multispectral remote sensing combined with machine learning methods to predict the SPAD values of litchi fruits [13]. Color indices and texture indices extracted from RGB images have also been used for monitoring SPAD [14]. Liu et al. linked 21 color indices calculated from UAV-acquired RGB images to barley SPAD values, thereby constructing a barley SPAD monitoring model [15]. Moreover, with the rise in multi-source information fusion methods in recent years, integrating data from different platforms and sensors can significantly improve the accuracy of phenotypic monitoring. For example, the multi-source data fusion of image texture features and spectral reflectance data has notably enhanced the estimation of crop leaf nitrogen content [16]. The fusion of spectral and texture indices derived from UAV multispectral images enables the more effective inversion of SPAD values in wheat canopies during the heading stage [17]. Mechanistic methods based on radiative transfer models have been widely applied in crop phenotyping monitoring. Some scholars used UAV multispectral images and the PROSAIL model to

remove canopy shadows, thereby improving the estimation accuracy of chlorophyll content in individual apple leaves [18]. Other scholars also estimated the chlorophyll content at the apple tree canopy scale using 3D radiative transfer models and UAV multispectral images [19]. In recent years, machine learning algorithms have played an important role in data modeling for crop phenotypic monitoring, such as random forest, partial least squares, and extreme gradient boosting regression. Some scholars have established chlorophyll content estimation models for wheat [20], maize [21], and cotton [22] based on SVR and RF algorithms, which exhibit better accuracy and robustness compared with traditional model construction methods. Therefore, it is necessary to investigate the combination of machine learning algorithms and multi-source data fusion to develop more accurate and efficient rice SPAD monitoring models.

To explore and evaluate the potential of multi-sensor data from phenotyping robot platforms combined with machine learning algorithms in phenotypic monitoring, as well as to improve monitoring accuracy, this study takes multispectral and RGB cameras as examples to investigate the application potential of multi-sensor data fusion in rice SPAD monitoring and to enhance the accuracy of rice SPAD monitoring by integrating machine learning algorithms. The main contributions of this research are as follows: (1) evaluating the feasibility of estimating rice SPAD using multi-sensor data from phenotyping robot; (2) analyzing the impacts of different input features and various machine learning algorithms on the accuracy of rice SPAD estimation; (3) constructing a high-precision and robust model for SPAD monitoring by integrating multi-sensor data from phenotypic robots with machine learning algorithms. In summary, this study provides a convenient, rapid, and accurate method for rice SPAD monitoring.

2. Materials and Methods

To monitor rice SPAD values using multi-source data from multispectral and RGB images acquired by a phenotyping robot, two ecological sites were selected for rice nitrogen experiments. We collected multispectral and RGB images at the jointing, heading, and filling stages, respectively, and concurrently measured SPAD values. Vegetation indices were extracted from multispectral images, while color indices and texture features were derived from RGB images. Subsequently, four machine learning algorithms—random forest regression (RF), partial least squares regression (PLSR), extreme gradient boosting (XGBoost), and gradient boosting regression trees (BRT)—were employed to construct models for monitoring rice SPAD values through multi-source data fusion. The overall workflow of the research content in this paper is illustrated in Figure 1.

2.1. Experimental Setup

The experiments conducted in this study were located in Rugao City (32°15′0.1″N, 120°45′43.8″E) and Taixing City (32°14′30.876″N, 120°14′48.408″E), Jiangsu Province. Both Rugao and Taixing feature a subtropical monsoon climate. We illustrate the layout of the experimental plots in Figure 2, and summarize additional details of the experiments in Table 1.

In the Rugao region, 36 experimental plots were established, whereas 24 plots were set up in the Taixing experiment. Both experiments incorporated nitrogen gradient treatments and different rice varieties. Specifically, the plot size in Rugao was 4 × 6 m, with three nitrogen application rates (0, 150, and 300 kg/ha) applied in a basal–topdressing ratio of 4:2:2:2. Two rice cultivars, Nangeng46 and Yongyou1540, were planted at densities of 30 × 15 cm and 50 × 15 cm. In Taixing, the plot size was 6 × 8 m, with five nitrogen levels (0, 240, 270, 300, and 330 kg/ha), using the same basal–topdressing ratio. Three rice cultivars (Huruang1211, Yanjing15, and Nangeng9108) were planted at densities of 18 × 25 cm,

14 × 25 cm, and 12 × 25 cm. Other field management practices in both locations adhered to local high-yield cultivation protocols. This experimental design allowed for comprehensive evaluations of the interactive effects of nitrogen management, planting density, and rice variety on crop performance under subtropical monsoon climate conditions.

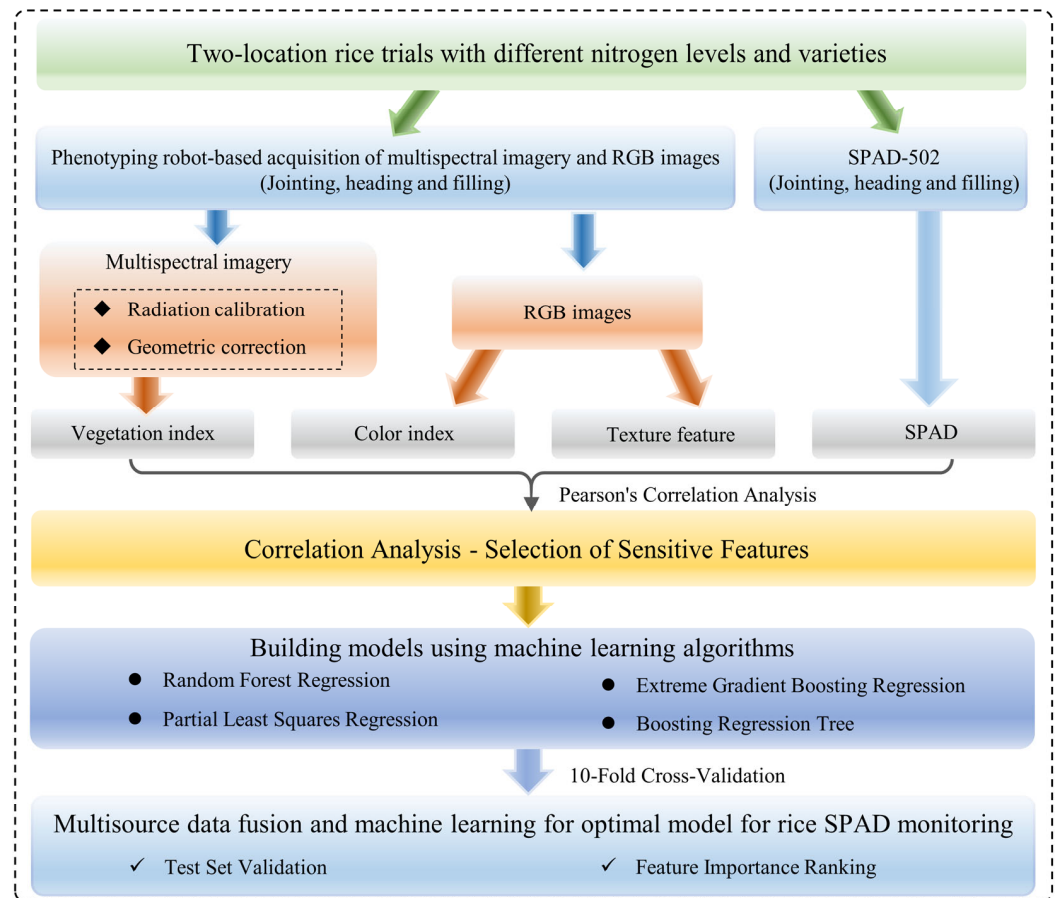


Figure 1. The flowchart of this study.

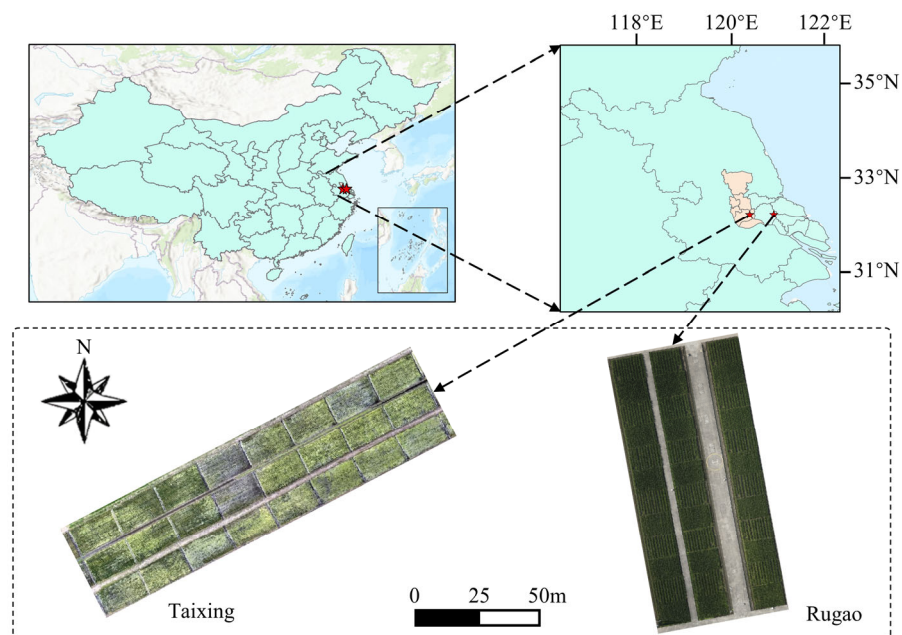


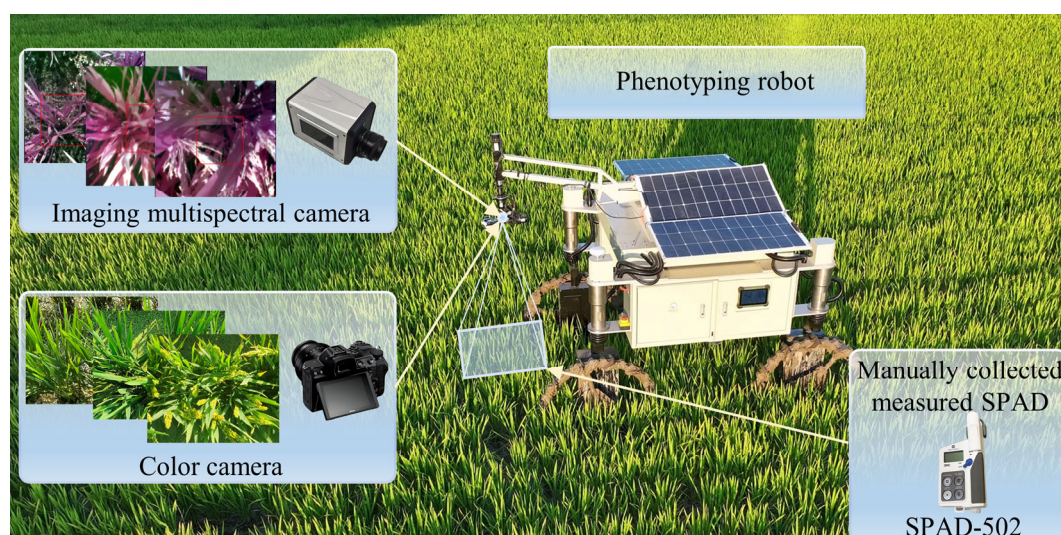
Figure 2. Diagram of experimental setup.

Table 1. Experiment information.

Experiment	Sowing Date	Sampling/Testing Date	Growth Period
2024 in Rugao	14 June	4 August	Jointing Stage
		1 September	Heading Stage
		30 September	Filling Stage
2024 in Taixing	30 June	7 August	Jointing Stage
		2 September	Heading Stage
		3 October	Filling Stage

2.2. Data Collection

The phenotyping robot employed in this study was independently developed by our laboratory in previous research. It is capable of operating in both paddy fields and upland environments, featuring adjustable wheelbases and the versatility to carry multiple sensors [23]. Equipped with a multi-spectral imager and an RGB camera, this robotic platform was utilized to collect data during the jointing, heading, and grain-filling stages of rice growth across two experimental sites. Concurrently, SPAD values were measured, as illustrated in Figure 3. Data collection activities were carried out between 10:00 and 13:00 on clear, windless days to ensure optimal conditions. The multi-spectral imager used is a mosaic snapshot-type device developed in-house, capable of simultaneously capturing eight spectral bands (467, 474, 527, 566, 679, 717, 731, 822 nm, with bandwidths ranging from 12 to 20 nm) in a single exposure. This design ensures the perfect spatial alignment of the multi-band images. Radiometric calibration was performed prior to each data acquisition session, and three replicate images were captured for each experimental plot. The RGB camera used was a Nikon Z5 (Nikon Co., Yokohama, Japan) model with a 24–70 mm F4 lens fixed at 50 mm focal length, maintaining consistent settings to ensure data consistency. Both sensors were mounted on a stabilized gimbal of the phenotypic robot, positioned 50–60 cm above the crop canopy to avoid shadows and ensure uniform data collection.

**Figure 3.** Data collection scenes using the phenotyping robot.

The SPAD values of rice leaves were measured using a SPAD-502 chlorophyll meter (Konica Minolta Co., Tokyo, Japan). This portable handheld device enables the rapid, non-destructive assessment of relative chlorophyll content in plant leaves by measuring

light transmittance at wavelengths of 650 nm and 940 nm. Measurements were taken at the same locations where spectral data and RGB images were collected. For each plot, a “five-point sampling method” was adopted, involving 10 randomly selected rice plants. Measurements were targeted at the upper, middle, and lower parts of each leaf, avoiding leaf veins. The average of these measurements was calculated to determine the leaf SPAD value for each plot.

2.3. Data Processing and Feature Extraction

2.3.1. Extraction of Vegetation Index

ENVI (Boulder, CO, USA) was employed for image cropping, ROI (Region of Interest) selection, and reflectance calculation. Specifically, the ENVI 5.3 software was utilized to extract the spectral reflectance values of each band from the preprocessed multispectral images. In this study, various vegetation indices (VIs) were used as inputs for developing the SPAD inversion model. Among the eight available bands, five bands with central wavelengths of 474, 566, 679, 717, and 822 nm were selected as the band data for subsequent analyses. Based on these selected bands, commonly used VIs were calculated to serve as inputs for machine learning, as illustrated in Table 2.

Table 2. Formulas for vegetation indices.

Spectral Indices	Formulations	Reference
RVI (Ratio Vegetation Index)	NIR/R	[24]
CIgreen (Green Chlorophyll Index)	$\text{NIR}/G - 1$	[25]
Clrededge (Red-Edge Chlorophyll Index)	$\text{NIR}/RE - 1$	[25]
MDD (Modified Double Difference Index)	$(\text{NIR} - RE) - (\text{NIR} - R)$	[26]
Int1 (Intensity Index 1 red-edge 1)	$(G + R)/2$	[27]
Int2 (Intensity index 1 Red-Edge 2)	$(G + \text{NIR} + R)/2$	[27]
Red-Edge NDVI (Red-Edge versions of SR and NDVI)	$(\text{NIR} - RE)/(\text{NIR} + RE)$	[28]
GARI (Green Atmospherically Resistant Vegetation Index)	$\text{NIR} - [G - (B - R)]$	[29]
SIPI (Structure Insensitive Pigment Index)	$(\text{NIR} - B)/(\text{NIR} + R)$	[24]
ARVI (Atmospherically Resistant Vegetation Index)	$[\text{NIR} - (R - 2(B - R))]/[\text{NIR} + (R - 2(B - R))]$	[24]
EVI (Enhanced Vegetation Index)	$2.5(\text{NIR} - R)/(\text{NIR} + 6R - 7.5B + 1)$	[30]
GNDVI (Green Normalized Difference Vegetation Index)	$(\text{NIR} - G)/(\text{NIR} + G)$	[30]
NDVI (Normalized Difference Vegetation Index)	$(\text{NIR} - R)/(\text{NIR} + R)$	[30]
SAVI (Soil-Adjusted Vegetation Index)	$1.5(\text{NIR} - R)/(\text{NIR} + R + 0.5)$	[30]
VARI (Visualization Atmospheric Resistance Index)	$(G - R)/(G + R - B)$	[30]

2.3.2. Color Index Extraction

The average grayscale values were extracted from the red, green, and blue channels of each sampling point in the RGB images using ENVI 5.3. These grayscale values were normalized to obtain standardized values (r , g , and b), which were then used to calculate various color indices (CIs) as shown in Table 3. Equations (1)–(3) were used to calculate the normalized values (r , g , and b).

$$r = \frac{R}{(R + G + B)} \quad (1)$$

$$g = \frac{G}{(R + G + B)} \quad (2)$$

$$b = \frac{B}{(R + G + B)} \quad (3)$$

where R , G , and B are the DN values of the red, green, and blue wavebands, respectively. In this study, seven common CIs were used to analyze the relationship with SPAD.

Table 3. Formulas for color indices.

Spectral Indices	Formulations	Reference
NDI (Normalized Difference Index)	$(g - r)/(g + r)$	[31]
ExG (Excess Green Index)	$2g - r - b$	[32]
ExR (Excess Red Index)	$1.4r - g$	[32]
ExGR (Excess Green Minus Excess Red)	$ExG - ExR$	[32]
VARI (Visible Atmospherically Resistant Index)	$(g - r)/(g + r - b)$	[33]
GLI (Green Leaf Index)	$(2g - r - b)/(2g + r + b)$	[34]
WI (Woebbecke Index)	$(g - b)/(r - g)$	[31]

2.3.3. Extraction of Texture Features

In this study, the Gray-Level Co-Occurrence Matrix (GLCM) was employed as the texture feature. GLCM is widely recognized as a statistical method for describing the spatial correlation of grayscale levels [35], and it plays a crucial role in establishing quantitative relationships with physiological parameters. In this study, GLCM was computed using ENVI software. Detailed texture information was determined by setting four key parameters within adjacent windows: (1) the smallest window size (rows $\times$ columns = 3 $\times$ 3) was adopted to provide detailed texture information; (2) the moving distance was set to 1 pixel; (3) the moving directions included angles of 0°, 45°, 90°, and 135°, with the 45° direction selected for calculation since its grayscale values are close to the average grayscale values of the four directions [35]; and (4) the highest grayscale quantization level of 64 (including four levels: 0, 16, 32, and 64) was chosen to ensure the high quality of GLCM.

Eight texture features from the red, green, and blue bands were extracted from the GLCM, namely mean (MEA), variance (VAR), homogeneity (HOM), contrast (CON), dissimilarity (DIS), entropy (ENT), second moment (SEM), and correlation (COR). For the convenience of subsequent analyses, these texture features were labeled with prefixes such as “R-”, “G-”, and “B-” to indicate that they were extracted from the three channels based on the GLCM (for example, “B-Con” represents the contrast of the blue band).

2.4. Model Construction and Evaluation

IBM SPSS Statistics 25 (IBM Corp., Armonk, NY, USA) was utilized to analyze the experimental data of rice SPAD, aiming to explore the correlations between three types of features and SPAD. By quantifying the degree of association among features, this analysis helped identify redundant information, optimize feature selection, and determine the most sensitive features to SPAD values. These selected features were then used as inputs for machine learning algorithm models, providing a basis for subsequent modeling.

The chosen features were further integrated into predictive models using Random Forest (RF), Partial Least Squares (PLS), Extreme Gradient Boosting (XGBoost), and Boosted Regression Trees (BRT) methods, all of which were implemented using the sklearn library in Python 3.8. During the algorithm training process, 70% of the data was used as the training set and 30% as the validation set. A 10-fold cross-validation approach was adopted, and grid search was employed to obtain the optimal model parameters.

Random Forest is an ensemble algorithm that reduces overfitting by averaging predictions from multiple decision trees. It involves preprocessing data, training trees on bootstrapped subsets with random feature selection, aggregating outputs, and optimizing via parameters like tree depth. Its random sampling of samples and features ensures high accuracy and robustness, suited for nonlinear and high-dimensional data.

Partial Least Squares Regression integrates principal component analysis and linear regression to handle multicollinearity by extracting latent variables correlated with the dependent variable. It standardizes data, extracts components (count via cross-validation),

evaluates fit with residuals, and interprets relationships through loadings, simplifying models while preserving key correlations.

Extreme Gradient Boosting, an optimized gradient boosting method, uses regularization to control complexity and second-order derivatives for faster convergence. It processes data as DMatrix, tunes hyperparameters via grid search, trains trees iteratively with early stopping, and evaluates via metrics like RMSE, enhancing speed and stability.

Boosted Regression Trees iteratively trains decision trees to correct prior errors, following the “weak learner integration” principle. It prepares data, initializes weak learners, adjusts weights by residuals, optimizes via cross-validation, and explains impacts via partial dependence plots. It excels at nonlinear relationships with minimal tuning and high interpretability.

The coefficient of determination (R^2) and root mean square error (RMSE) were used as two accuracy evaluation metrics. The equations for these metrics are as follows.

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - y_i')^2}{\sum_{i=1}^n (y_i - \bar{y})^2} \quad (4)$$

$$RSME = \sqrt{\frac{\sum_{i=1}^n (y_i - y_i')^2}{n}} \quad (5)$$

where y_i and y_i' represent the measured values and predicted values of the samples, respectively; $\bar{y}$ denotes the mean of the measured values; and n is the number of samples.

3. Results

3.1. Statistical Analysis of SPAD

The analysis results of the SPAD values obtained in this study are presented in Table 4 and Figure 4. We collected a total of 180 data samples, with values ranging from 29.3 to 47.1 and an overall coefficient of variation (CV) of 8.5%. Specifically, the coefficients of variation at the jointing stage, heading stage, and filling stage were 6.7%, 6.5%, and 10%, respectively. Overall, the variability of SPAD values was relatively small, indicating a relatively uniform distribution across the samples. Figure 4 and Table 4 illustrate the distribution characteristics of the SPAD values of rice plants at different growth stages in this experiment. The constructed model can demonstrate the spatial variability within the experimental field.

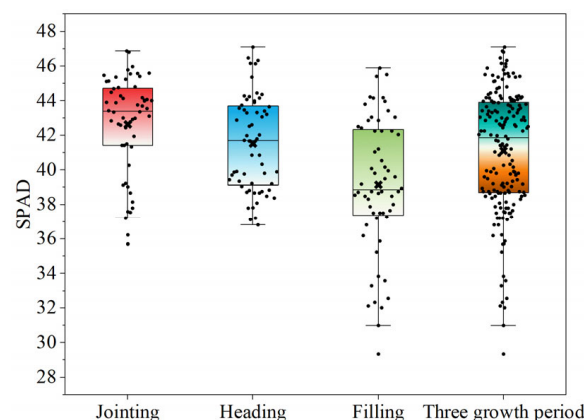


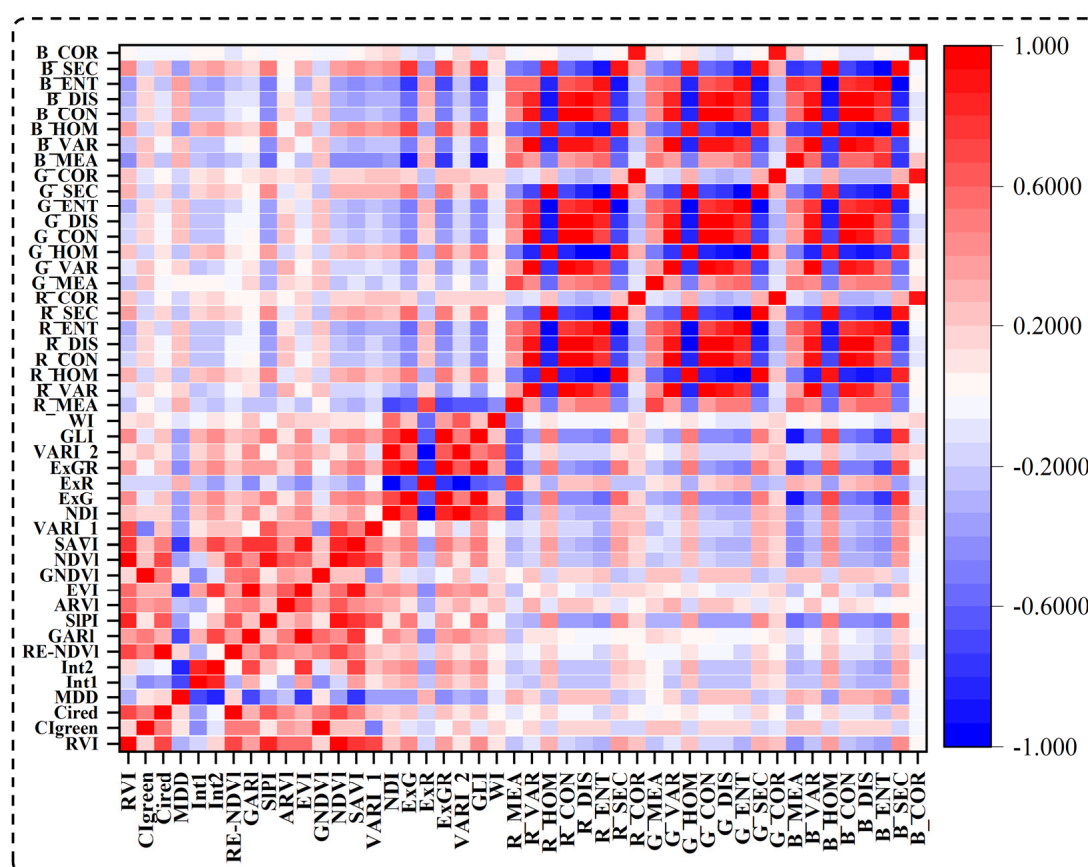
Figure 4. Boxplot of SPAD data.

Table 4. Summary SPAD statistics for four crops.

	Sample Size	Maximum	Minimum	Mean	Standard Deviation	Variance	CV
Three growth period	180	47.10	29.34	41.10	3.52	12.42	0.085
Jointing	60	46.87	35.67	42.63	2.88	8.34	0.067
Heading	60	47.1	36.81	41.53	2.73	7.47	0.065
Filling	60	45.9	29.34	39.13	3.92	15.36	0.101

3.2. The Correlation of Characteristic Parameters to SPAD

A Pearson correlation analysis was performed of SPAD values and vegetation indices, color indices, and texture features, as well as among the features themselves. The correlation analysis results among features are shown in Figure 5, and the correlation results comparing features and SPAD are presented in Figure 6.

**Figure 5.** Heatmap of correlations between features.

Vegetation indices showed the strongest overall correlation, followed by color indices, while texture features had the weakest correlation. The correlation coefficients of vegetation indices ranged from 0.254 to 0.809, with NDVI being the feature with the highest correlation. For color indices, the correlation coefficients ranged from 0.241 to 0.63, and the color index with the highest correlation was WI. As for texture features, their correlation coefficients ranged from 0.182 to 0.428, among which the B_Homogeneity feature had the highest correlation. Finally, the top 8 vegetation indices, 5 color indices, and 10 texture feature parameters with the highest correlations were selected as the input feature set for the model.

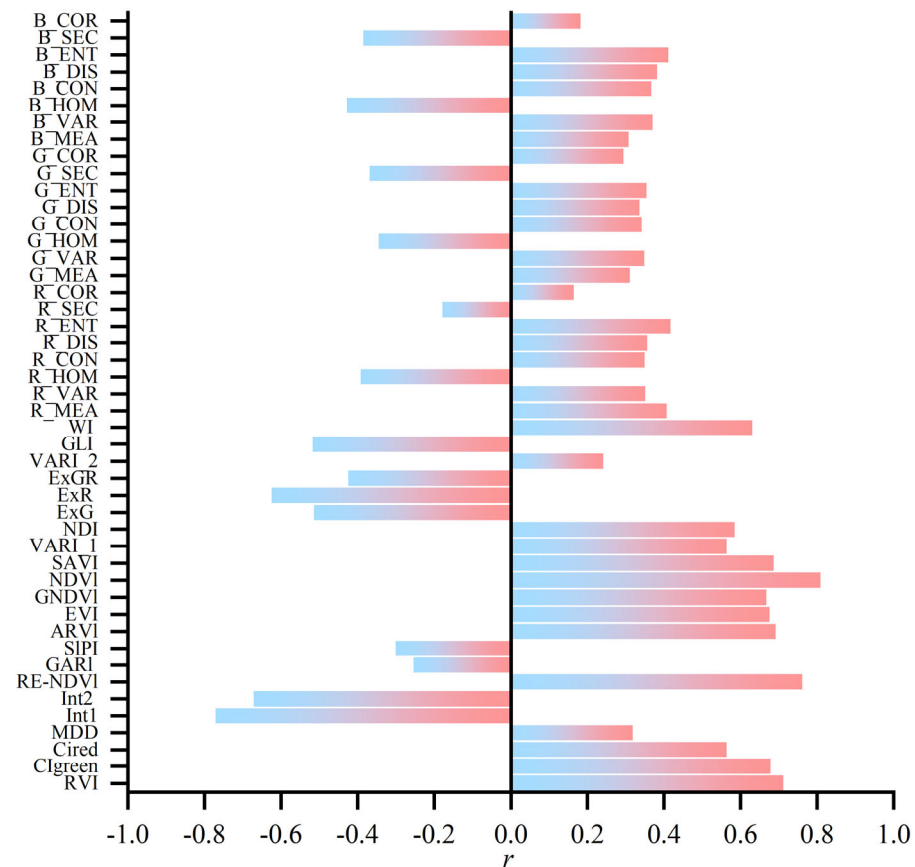


Figure 6. Heatmap of correlations between SPAD and features.

3.3. Evaluation of SPAD Monitoring Model Based on Machine Learning and Multi-Sensor Data

A combination of four machine learning algorithms and parameter optimization was used to establish quantitative relationships between the feature information and SPAD values of rice at three growth stages, thereby developing robust models for estimating SPAD. Three machine learning models were trained using the optimal algorithm and parameters for each type of feature, and one machine learning model with optimized parameters was trained through the fusion of the three types of features. Table 5 presents the results of the constructed SPAD monitoring models, including those for the 70% training set and 30% test set. All models were built using data from the three growth stages as input. Models trained with four different machine learning algorithms using single-type features showed that vegetation indices yielded relatively high accuracy ($R^2 = 0.67\sim 0.78$). Specifically, the combination of vegetation indices and Random Forest (RF) achieved the best performance among single-type features, with an R^2 of 0.78. Models trained with color indices exhibited moderate accuracy ($R^2 = 0.61\sim 0.70$), while those trained with texture features performed the poorest ($R^2 = 0.55\sim 0.64$). Models based on the fusion of the three types of features achieved the highest accuracy in rice SPAD estimation ($R^2 = 0.75\sim 0.83$), with all four machine learning algorithms outperforming their counterparts trained with single-type features. Among them, the RF algorithm achieved an R^2 of 0.83 and an RMSE of 1.593; the Partial Least Squares (PLS) algorithm had an R^2 of 0.75; the Extreme Gradient Boosting (XGBoost) algorithm reached an R^2 of 0.80; and the Boosted Regression Trees (BRT) algorithm obtained an R^2 of 0.78. The rice SPAD monitoring model based on the RF algorithm across all growth stages demonstrated higher predictive accuracy, characterized by a higher R^2 value and a lower RMSE value. Among the models trained with four different feature inputs using the four machine learning algorithms, the RF model consistently maintained the best performance, while the other three algorithms showed a relatively balanced performance

across different inputs. It is noteworthy that the XGBoost model performed exceptionally well on the 70% training set, with an R^2 of 1.0 in all cases, which may indicate overfitting or could be attributed to the inherent characteristics of the algorithm.

Table 5. Construction of SPAD prediction models.

Feature	Method	Validation Set		Training Set	
		R^2	RMSE	R^2	RMSE
Vegetation Index	Random Forest Regression	0.78	1.872	0.92	1.247
	Partial Least Squares Regression	0.67	3.080	0.83	2.107
	Extreme Gradient Boosting Regression	0.75	2.302	1	0.238
	Boosted Regression Tree	0.76	2.236	0.88	2.098
Color Index	Random Forest Regression	0.70	2.275	0.89	1.421
	Partial Least Squares Regression	0.61	3.020	0.72	2.662
	Extreme Gradient Boosting Regression	0.67	2.762	1	0.001
	Boosted Regression Tree	0.65	2.691	0.83	1.960
Texture features	Random Forest Regression	0.64	2.58	0.91	1.111
	Partial Least Squares Regression	0.55	2.992	0.69	2.331
	Extreme Gradient Boosting Regression	0.58	2.870	1	0.003
	Boosted Regression Tree	0.61	2.632	0.92	0.636
Integration of three features	Random Forest Regression	0.83	1.593	0.92	1.013
	Partial Least Squares Regression	0.75	2.399	0.79	2.230
	Extreme Gradient Boosting Regression	0.80	1.997	1	0.000
	Boosted Regression Tree	0.78	2.197	0.88	1.391

In the process of training machine learning algorithm models, grid search and cross-validation methods were employed to determine the optimal parameters for the models, aiming to achieve the best performance. For the machine learning models trained with the fusion of the three types of features, the results of the grid search are shown in Figure 7, where the ordinate represents RMSE. The RMSE was minimized through the optimization of model parameters.

Grid search was performed for the learning rate and n_estimators of the BRT model, with the learning rate ranging from 0 to 0.30 and n_estimators ranging from 100 to 1000 at intervals of 100. The optimal parameters were determined as 0.15 and 300, respectively. For the XGBoost model, grid search was conducted for n_estimators and max depth, with the search ranges set as 100 to 800 and 0 to 20, respectively; the optimal parameters were identified as 800 and 9. Regarding the RF model, optimization was performed for mtry and n_estimators via grid search, where mtry ranged from 0 to 1 and n_estimators ranged from 100 to 2100 at a step size of 200. The optimal values were found to be 0.82 and 300, respectively. For the PLS model, n_components was optimized within the range of 0 to 22, and the optimal number was determined as 20.

Figure 8 presents scatter plots of the optimal test set results for rice SPAD estimation models across the entire growth cycle, constructed using different input features and all based on the random forest algorithm. The results in the figure indicate that the developed estimation models exhibit a relatively stable inversion performance for rice SPAD ($R^2 = 0.64\sim 0.83$). The integration of multi-sensor data with machine learning algorithms proves to be an effective approach for improving SPAD inversion accuracy, among which the SPAD estimation model built by combining RF with three types of features achieves the highest precision ($R^2 = 0.83$). Additionally, the figure includes a fitting verification for each growth stage, revealing that the SPAD inversion accuracy is relatively high during the heading stage, with R^2 values ranging from 0.74 to 0.88 across RF models with different feature inputs.

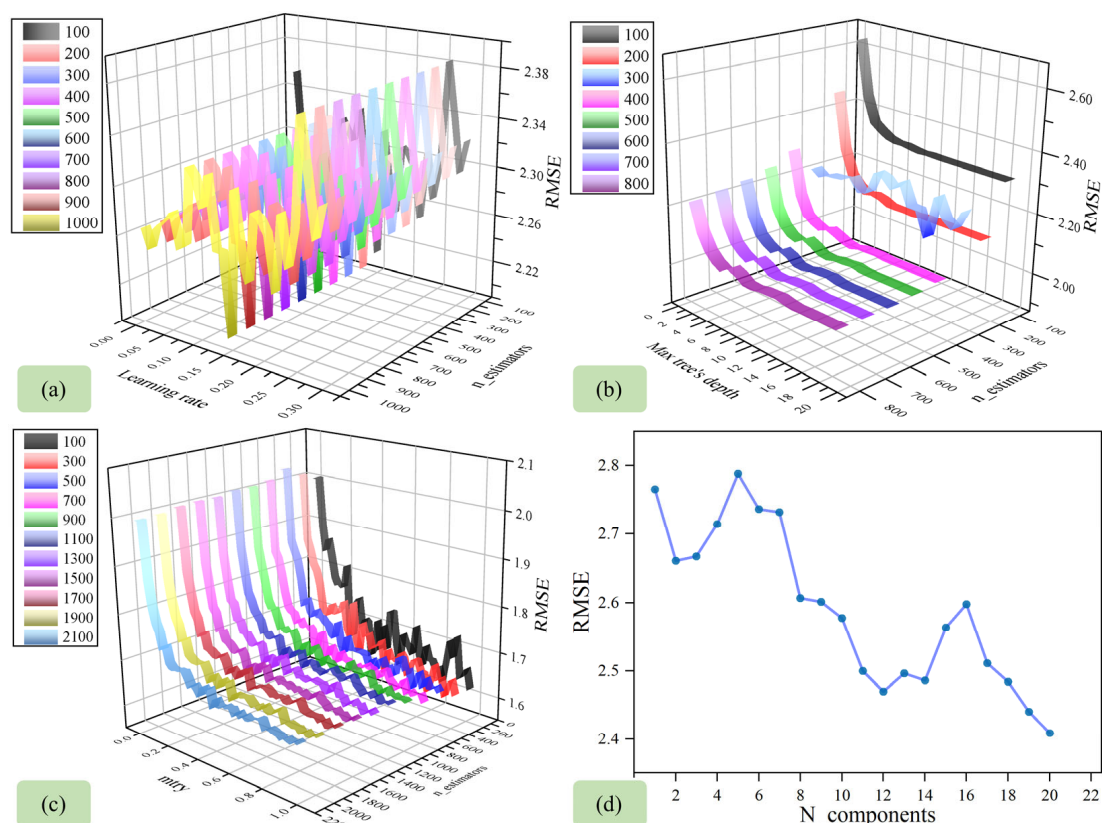


Figure 7. Optimization of machine learning models: (a) BRT, (b) XGBoost, (c) RF, and (d) PLSR.

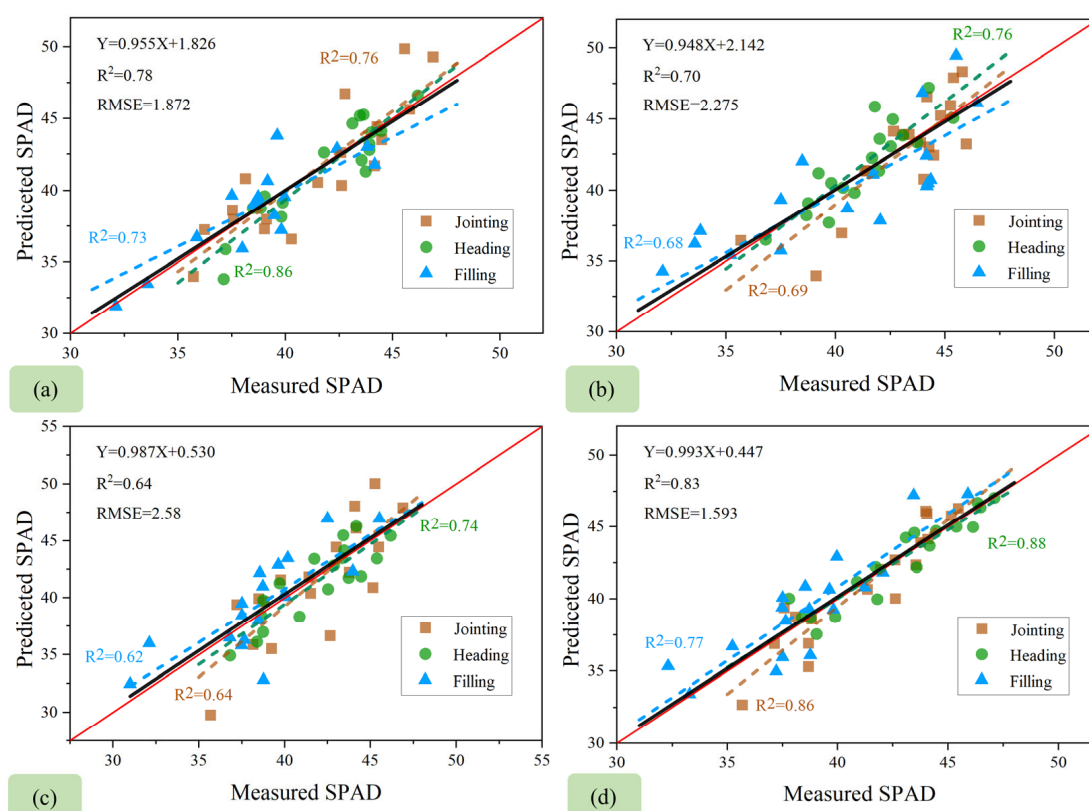


Figure 8. 10-fold cross-validation results of RF models with different feature inputs: (a) vegetation index, (b) color index, (c) texture features, and (d) the integration of these three features.

In the rice SPAD estimation model constructed using the RF algorithm with the fused input of three types of features, Gini Importance values were employed to evaluate the contribution of each input feature to the model, as shown in Figure 9. The range of the Gini importance values is between 0 and 1. Among them, the Gini importance values of NDVI and Int1 are the highest and the second highest. The range of Gini importance values is between 0 and 1, among which the Gini importance value of G_SEC is the lowest. Among the feature types, vegetation indices contributed the most to the model, followed by color indices, with moderate contributions, while texture features made the lowest contribution. These findings highlight the importance of integrating vegetation indices, color indices, and texture features to enhance the accuracy and robustness of rice SPAD monitoring models.

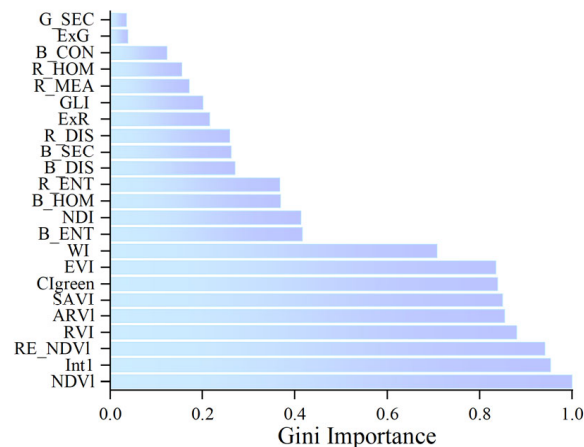


Figure 9. Ranking of Gini Importance values.

The results of the feature sensitivity analysis for the random forest model with three features co-input are shown in Figure 10. The ordinate in the figure is R^2 , and the abscissa represents the input features of the model. The R^2 of this optimal model is 0.83. DropScore refers to the performance metric obtained on the validation set after removing a specific feature from the training set and retraining the model. Delta is the contribution value of the feature, and a larger Delta indicates that the feature is more critical. It can be seen from Figure 9 that the feature with the highest contribution is NDVI, with a Delta of 0.147, while the one with the lowest contribution is EXG, with a Delta of 0.073. The results in Figure 10 are generally consistent with those in Figure 9, which can indicate the sensitivity and variability of different input features.

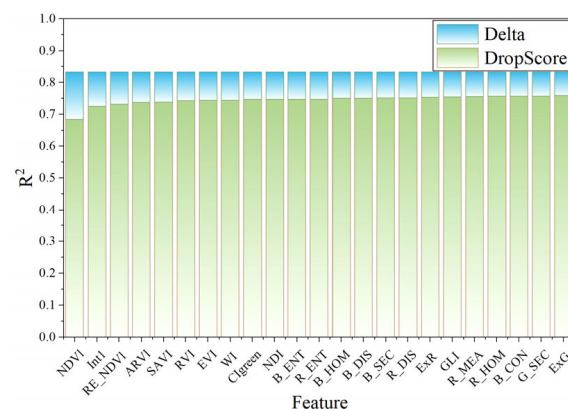


Figure 10. Ranking of feature sensitivity analysis.

4. Discussion

The introduction of such phenotyping robots as data collection platforms offers numerous advantages over traditional manual sampling or fixed-equipment-based methods, including a high degree of automation, repeatability, and flexible operation in complex field environments. Compared with UAV platforms, they can be equipped with multiple sensors to enable phenotypic monitoring using multi-sensor data. Moreover, the data acquired are at close range and of high resolution, providing high-quality data for phenotypic monitoring. The phenotyping robot described in this study is equipped with two sensors and operates according to a pre-set program, allowing it to accurately and efficiently acquire multispectral images and RGB photos of rice at different growth stages. Specifically, multispectral images capture the reflection information of rice across different spectral bands, thereby reflecting its physiological and biochemical characteristics, while RGB images provide intuitive visual texture and color information. The fusion of these two data sources can comprehensively describe rice canopy features from multiple dimensions, offering a reliable means for the long-term dynamic monitoring of SPAD value changes during rice growth. Instead of traditional modeling methods, this study employs advanced machine learning algorithms to construct rice SPAD monitoring models. As a data-driven modeling approach, machine learning can overcome the limitations of traditional empirical models, thereby improving the accuracy of SPAD value estimation. Four algorithms are utilized: random forest regression, partial least squares regression, extreme gradient boosting regression, and boosted regression trees. Among them, random forest regression achieves the highest accuracy in models constructed with different data inputs, demonstrating the superiority and applicability of this machine learning algorithm. Specifically, the monitoring model built by inputting three types of features—vegetation indices from multispectral images, color indices from RGB images, and texture features—into the random forest algorithm yields an R^2 of 0.83. This validates that the integration of multi-sensor data from phenotyping robot platforms with machine learning algorithms is an effective and practical method for monitoring rice SPAD. In SPAD estimation, machine learning-driven methods do not require knowledge of physical mechanisms, and they exhibit strong adaptability for multi-source feature fusion, ease of implementation, and high accuracy, but they rely on sample distribution. Physics-based methods have good interpretability but depend on high-precision data and professional knowledge, resulting in poor generalizability. Hybrid methods achieve a good balance but involve complex coupling design and face difficulties in practical application. The machine learning-based multi-source feature integration method proposed in this study is more suitable for practical agricultural monitoring needs.

A notable limitation of this study lies in the relatively limited sample size during model construction and validation, which may compromise the generalization ability and stability of the machine learning models to a certain extent. Although the existing samples cover combinations of different nitrogen gradients, varieties, and planting densities across the two experimental sites, the overall sample size remains insufficient to fully support complex machine learning algorithms in deeply exploring the underlying patterns in the data. This issue is particularly prominent when the data contain noise, feature dimensions are high, or there is a local imbalance in sample distribution—circumstances under which a small sample size may lead to model overfitting to the training data. Evidence of this is presented in Table 5, where the R^2 values of the extreme gradient boosting model reach 1 for the training set, yet the model fails to achieve satisfactory accuracy for the test set. This study constructed SPAD monitoring models using data from the entire growth period of rice. The results of SPAD estimation models built for different rice growth stages—using three types of feature fusion and four distinct machine learning algorithms—are presented in Figure 11. As shown in the figure, the accuracy of SPAD retrieval was highest during the heading

stage. Compared with the jointing and grain-filling stages, rice leaves at the heading stage exhibit peak chlorophyll content, with fully expanded leaves of uniform thickness. This minimizes interference from mesophyll structure on spectral signals, while soil background reflection interference is nearly eliminated, allowing the spectra to primarily reflect the true signals of the leaves. At the level of machine learning algorithms, the random forest regression model outperformed the other three models, with PLSR showing the poorest performance. This finding is consistent with the results reported by other scholars [36,37].

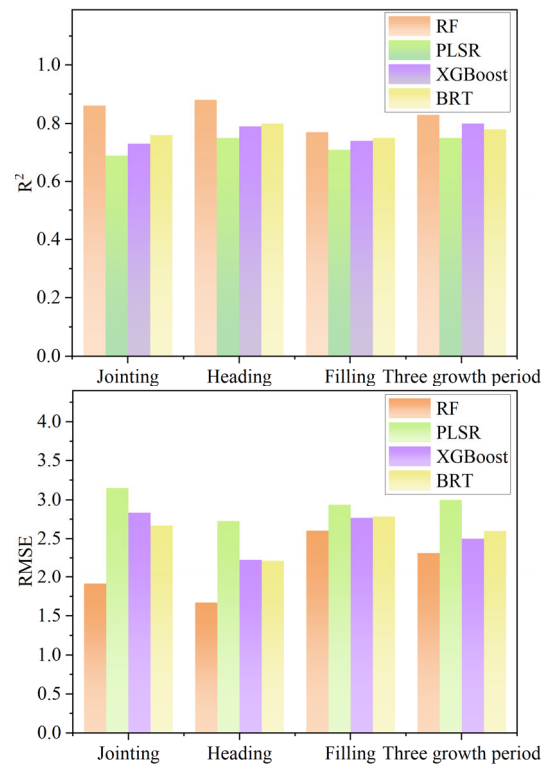


Figure 11. R^2 and RMSE of four machine learning models with three feature fusion inputs across different growth stages.

Further expanding the dataset—for instance, by incorporating experimental data from more years and diverse climatic regions, or increasing the frequency of sampling throughout the growth period in existing experiments—would provide machine learning models with richer feature distribution information and broader scenario coverage. Sufficient data not only reduces the interference of random errors in model training but also enhances the model's ability to analyze different growth stages. This enables algorithms to more accurately identify the nonlinear relationships between multi-source data and SPAD values, ultimately improving model robustness and providing more reliable technical support for large-scale, high-precision SPAD estimation. In subsequent studies, broader multi-source feature fusion could be employed by integrating climatic factors and soil property data with the existing multispectral and RGB data. Such environmental and soil data can explain variations in rice physiological status from a mechanistic perspective, complementing spectral and visual features to help the model more comprehensively capture the driving factors of SPAD values. Compared with traditional machine learning methods, deep learning exhibits stronger automatic feature extraction capabilities, making it particularly suitable for processing multi-source heterogeneous data. Through hierarchical feature learning, deep learning can excavate hidden high-order correlations within the data, further improving the prediction accuracy and generalization ability of SPAD values in complex agricultural scenarios. By combining expanded datasets, multi-source feature fusion, and

deep learning algorithms, it is expected that a more robust SPAD estimation model can be developed, offering more powerful technical support for crop growth monitoring and precision fertilization.

5. Conclusions

Multispectral images and RGB images of rice across multiple growth stages were acquired via a phenotyping robot. By extracting vegetation indices, color indices, and texture features from these images, and integrating multi-sensor data with machine learning algorithms, the effective monitoring of rice SPAD was achieved. Specifically, the fusion of the three feature types outperformed single-type features, and the Random Forest regression algorithm exhibited superior performance compared to the other three machine learning algorithms. The constructed SPAD monitoring model yielded an R^2 of 0.83 and an RMSE of 1.593. Moreover, the heading stage achieved higher accuracy than the jointing and filling stages. In conclusion, the method proposed in this study is characterized by automation, high efficiency, and non-destructive monitoring, which can provide technical support and a theoretical foundation for rice phenotyping monitoring and precision crop cultivation management.

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