COUPLING UNMANNED AERIAL VEHICLE (UAV) MULTISPECTRAL IMAGERY AND INTEGRATED LEARNING TO CONSTRUCT A MONITORING AND PREDICTION MODEL FOR RELATIVE CHLOROPHYLL CONTENT (RCC) AND LEAF AREA INDEX (LAI) OF SORGHUM IN FIELDS
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基于无人多光谱图像和集成学习的田间高粱叶绿素相对含量与叶面积指数的监测预测模型

Qi LIU, Huping LIU, Mengjiao XU, Lian BAI, Wuping ZHANG[*)], Guofang WANG [2*)]
[1)] College of Software, Shanxi Agricultural University, Taigu, Shanxi / China
[2)] College of Resources and Environment, Shanxi Agricultural University, Taigu, Shanxi / China
Corresponding authors: Zhang Wuping; Tel: +86-15935664481; E-mail: zwping@126.com
Guofang Wang, Tel: +86-15835470561; E-mail: guofang19800104@126.com
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ABSTRACT
This study mainly investigates the feasibility of monitoring and estimating the RCC (Relative Chlorophyll Content) and the LAI (Leaf Area Index) of sorghum by coupling integrated learning model with UAV multispectral image, clarifies the quantitative relationship between RCC and LAI of sorghum and the vegetation index based on different spatial resolutions, and constructs a Monitoring and prediction model for the RCC and the LAI of sorghum based on the UAV multispectral image and the vegetation index at different spatial resolutions. The model constructed based on integrated learning, and using the stacking approach had good prediction accuracies at three spatial resolutions, with the stacking model predicting R^2=0.87, MAE=18.27, and RMSE=22.23 for the RCC at spatial resolution of 0.017 m; R^2=0.86, MAE=17.38, and RMSE=23.21 for RCC at spatial resolution of 0.024 m; R^2=0.80, MAE=18.62, and RMSE=24.12 for RCC at spatial resolution of 0.030 m; R^2=0.93, MAE=0.34, and RMSE=0.37 for LAI at spatial resolution of 0.017 m; and R^2=0.89, MAE=0.44, and RMSE=0.55 for LAI at spatial resolution of 0.024 m. The model established by combining the vegetation index and integrated learning can quickly and accurately monitor and predict RCC and LAI of sorghum, which provides a scientific methodology and theoretical basis for scientific monitoring and predicting RCC and LAI of sorghum in the field.

摘要
本研究主要探讨了将集成学习模型与无人机多光谱影像耦合，监测和估算高粱叶绿素相对含量和叶面积指数的可行性，明确了基于不同空间分辨率的高粱叶绿素相对含量和叶面积指数与植被指数之间的定量关系，构建了基于无人机多光谱影像和植被指数的不同空间分辨率高粱叶绿素相对含量和叶面积指数的预测模型。基于集成学习和堆叠方法构建的预测模型在三种空间分辨率下均具有良好的预测精度，其中堆叠模型在空间分辨率为 0.017m 时预测叶绿素相对含量的 R^2=0.87，MAE=18.27，RMSE=22.23；在空间分辨率为 0.024m 时预测叶绿素相对含量的 R^2=0.86，MAE=17.38，RMSE=23.21；空间分辨率为 0.030 m 时叶绿素相对含量的 R^2=0.80，MAE=18.62，RMSE=24.12；空间分辨率为 0.017m 时叶面积指数的 R^2=0.93，MAE=0.34，RMSE=0.37；空间分辨率为 0.024m 时叶面积指数的 R^2=0.89，MAE=0.44，RMSE=0.55。植被指数与集成学习相结合而建立的模型能够快速且准确地监测和预测高粱的叶绿素相对含量和叶面积指数，为科学监测、预测田间高粱的叶绿素相对含量和叶面积指数提供了科学的方法和理论依据。

INTRODUCTION
Sorghum [*Sorghum bicolor (L.) Moench*] is the fifth largest cereal crop in the world. It has a long history of cultivation in China, with high and stable yields and other characteristics, and has a unique drought-resistant, waterlogging-resistant, saline-resistant, barren, and other resistance to adversity, in the plains, hills, floodplains, saline and alkaline land. It can be planted with a variety of uses, such as food, brewing, feeding, energy, silage, etc., and the potential development of sorghum is huge.

The chlorophyll content is an important parameter to consider in crop growth. It has a direct relationship with the final yield, which can effectively reflect the growth status and nutritional status of crops *(Pan et al., 2023*). Therefore, rapid and accurate monitoring of the chlorophyll content of crops can provide a timely understanding of the crop growth status and can be used to make a scientific prediction of the final yield of crops (*Berjon et al., 2022*). LAI is an important physiological parameter reflecting the monitoring of crop phenotype (*Liu et al., 2012*). The vegetation index obtained by remote sensing technology for the calculation of the band has a strong correlation with the LAI; the use of remote sensing technology can be used in small and medium-sized areas of the crop LAI prediction, to provide a strong support for agricultural management (*Hunt et al., 2008*). The application of drones in crop monitoring is a hot spot in the current field of agricultural science and technology. With the rapid development of UAV technology, its application in precision agriculture is more and more extensive, especially in crop growth monitoring and management. UAV multispectral technology has a large number of applications in crop monitoring by applying the advantages of flexibility, simple operation, and ease of use *(Tavakoli et al., 2014)*.

Guo et al. found that the prediction effect of the prediction model established based on the support vector machine-based prediction model has the best prediction effect and also helps to retrieve SPAD values based on spectral and texture indices extracted from multispectral images using machine learning methods (*Guo et al., 2022*). Sudu B et al. inverted summer maize SPAD values using UAV hyperspectral data based on multiple machine learning algorithms, and the results showed that UAV hyperspectral image data can be used to predict maize growth information and that machine learning-based prediction models can quickly and non-destructively predict maize SPAD values (*Sudu et al., 2022*). Zhang et al. used an unmanned collection of hyperspectral images of winter wheat and multiple machine-learning models based on different algorithms to train an LAI inversion model *(Zhang et al., 2021)*. That shows UAV monitoring technology can accurately measure chlorophyll content and leaf area of field crops on a large scale and with high throughput, so effective monitoring of field sorghum can be realized by the means mentioned above.

However, most of the studies on growth monitoring and yield prediction of crops use vegetation indices, texture, and spectral information, but due to the differences in plant species, varieties, fertility periods, and research methods, the forms and parameters of the constructed models are different, which results in the conclusions obtained from a single experiment being often not universal (*Tunca et al., 2018*). The research on monitoring and prediction of sorghum-based on RGB images of drones has also been rarely reported, and fewer studies have been carried out on the optimal spatial resolution for monitoring. Few studies have been reported on the monitoring and predicting sorghum based on RGB images from UAVs, and fewer studies have been conducted on the optimal spatial resolution for monitoring. Because of this, this study, based on previous studies, with the advantage of UAV in variable spatial resolution, attempts to obtain multispectral images by UAV and combine them with vegetation indices under different spatial resolutions by using machine learning to build a model and combine them with the experimental data related to RCC and LAI of sorghum obtained during the same period to realize the prediction of important indices of sorghum growth at the field scale. By comparing the differences in generalization ability and prediction accuracy among models, the best prediction model is identified to provide new theoretical support and technical means for data collection, production management, and yield estimation in sorghum growth monitoring.

MATERIALS AND METHODS

Test Material and Test Site

The test sorghum variety is JINZA No.22. The test site is located in Wujiabao Village, Taigu County, Jinzhong City, Shanxi Province, China. The region (elevation 800 m, longitude 112° 30’ 51’’ E, latitude 37° 26’ 41’’ N) has a temperate continental monsoon climate, with high temperature and rain in summer, cold and dry in winter, and four distinct seasons, with an altitude of about 795~805 m above sea level and an average annual frost-free period of 160-190 days. The average annual temperature is 10.6℃, the annual precipitation is 400 mm-600 mm, the main precipitation is concentrated in July-August, and the average annual sunshine is 1810 hours-2100 hours, which is suitable for the growth of sorghum, one season a year. The experiment was sown by manual spot sowing, with sowing row spacing of 0.3 m and plant spacing of 0.2 m. The sowing time was April 25, 2021, and the harvest was made on October 13, 2021, and the test was carried out by selecting the stage of pulling out, tasseling, and ripening of sorghum, and the conventional field management such as watering, fertilizer, and spraying of herbicides were carried out at appropriate time according to the experience, to prevent the interference of its cause.

Data Acquisition and Processing

In this study, a multispectral camera modeled as MicaSense RedEdge-MX is used, which has five spectral bands, namely, blue, green, red, red-edge, and near-infrared. The device is mounted on the 4-axis UAV platform of the DJI Phantom 4 Pro to collect multispectral images. The system includes a flight control system, power supply system, stabilizing gimbal, remote control, display, etc. The image data are collected when the light intensity is moderate and the radiation is stable to ensure the accuracy of the collected image data. The multispectral sensors are calibrated before the start of the flight to ensure the accuracy of the multispectral image calibration. The RCC of the tested sorghums was determined using a hand-held portable chlorophyll meter (Instrument model: CM 1000, which has a range of values from 0-999) for chlorophyll determination. Four target sorghum plants were selected, and the RCC values of the top two fully expanded leaves were measured: a total of three parts of the leaf such as the leaf base, leaf middle, and leaf tip were measured, and a leaf was measured at least three times. Finally, all the measurements on the same leaf were averaged and taken as the RCC of the plant. The LAI of the tested sorghums was determined using a handheld portable leaf area meter (instrument model: LAI-2200C) using the modified LAI method.

The measurement of the relevant data was carried out simultaneously with the acquisition of multispectral photos by UAV to ensure the consistency of the collected data. Meanwhile, the UAV data measurements were carried out in a windless and cloudless period with suitable light to ensure the accuracy of the collected data. The valid data obtained during the experiment were divided into a training set and a validation set, in which the training set accounted for 70% and the validation set accounted for 30%. The processing and analysis of the data was done based on Python 3.6. The processing of the multispectral images acquired by the UAV was done through Agisoft PhotoScan and ArcGIS.

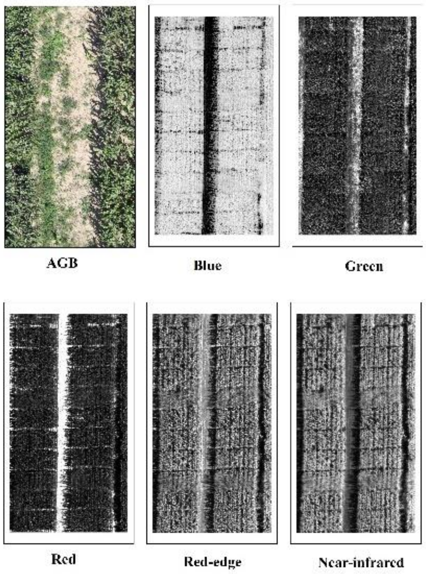

Fig. 1 - Multispectral images of unmanned aerial vehicles in different frequency bands of sorghum

Vegetation Indices Selection and Model Evaluation

Healthy green vegetation in the blue and red light band shows absorption, while in the green light and near-infrared band has a strong reflection. Hence, the vegetation index is the use of green vegetation in different bands of different characteristics, through the sensor obtained by the combination of different bands of information, to achieve the purpose of enhancing the vegetation information. It is essentially a comprehensive consideration of a variety of spectral information, and its certain mathematical transformations so that it enhances the vegetation information at the same time and minimizes the non-vegetation and other noise. There are hundreds of vegetation indices proposed in related research fields, and in this study, 11 vegetation indices that showed a high correlation with the RCC and LAI of the test species were selected.

Regarding the evaluation of the model prediction results, the coefficient of determination R^2, Mean Absolute Error (MAE), and Root Mean Square Error (RMSE) are used in this study.

RESULTS

Analysis of Variations in RCC and LAI at Different Flight Altitudes

In this section, data on variations in RCC and LAI obtained through multispectral imaging technology using UAVs at different flight altitudes are presented. Measuring RCC and LAI provides essential insights into the growth status and health of plants. Changes in these indicators can help farmers promptly identify issues such as nutrient deficiencies, pest infestations, or diseases, enabling them to take appropriate measures to protect plant health and promote high-quality crop yields.

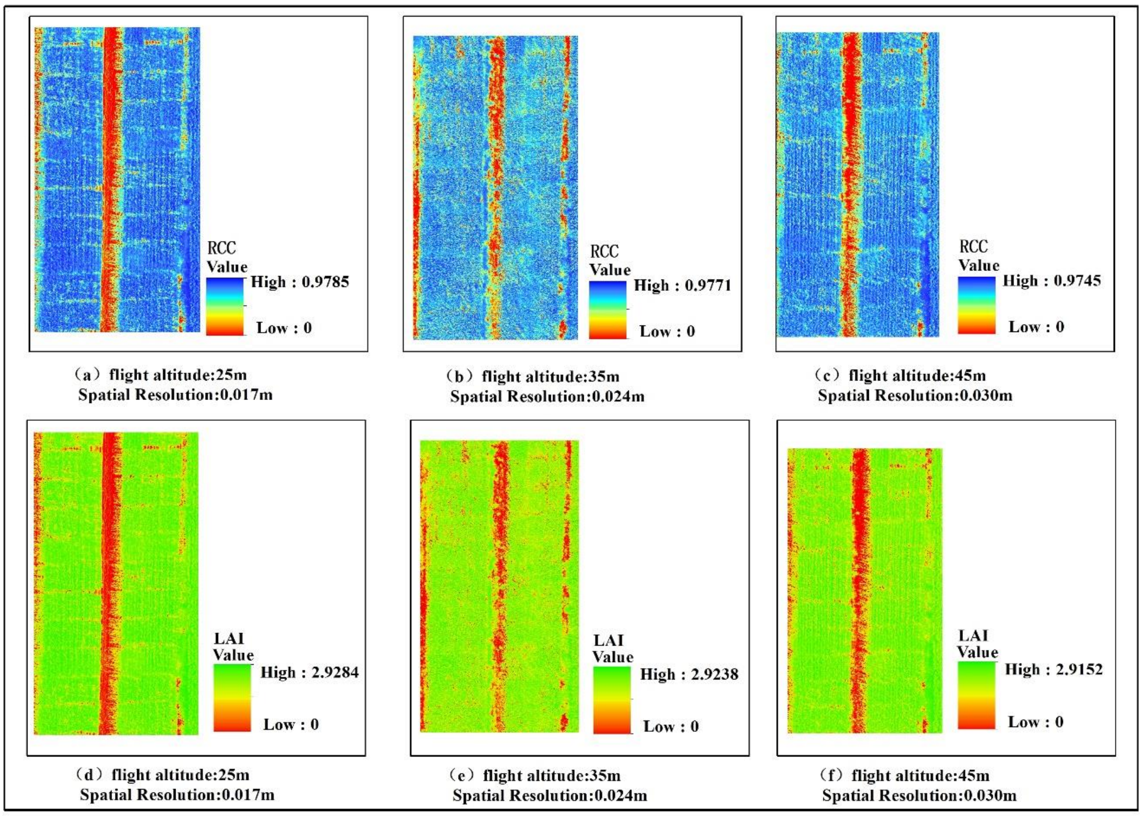

Fig. 2 - RCC and LAI spectra at different spatial resolutions

When the UAV flight altitude is 25 meters, the corresponding spatial resolution is 0.017 meters. At this spatial resolution, it was observed that the measured RCC and LAI values were 0.9785 and 2.9284, respectively, indicating that the health status of the plants is optimal at this height. As the flight altitude increases to 35 meters and 45 meters, the RCC and LAI values gradually decline, reaching 0.9771 and 2.9238 (at 35 meters), and 0.9745 and 2.9152 (at 45 meters), respectively. This trend suggests that higher flight altitudes may reduce the ability to capture vegetation characteristics, thereby affecting the accuracy of the monitoring data.

As shown in the figure 2, the variations in RCC and LAI measured at different flight altitudes are illustrated. The figure clearly indicates that RCC and LAI values are highest at a flight altitude of 25 meters, while both indicators show a declining trend as the flight altitude increases.

The reason for this variation may be attributed to increased light scattering and reflection at higher flight altitudes, which can affect the ability to capture vegetation characteristics. Additionally, higher altitudes may reduce the resolution of the sensors, making it more challenging to monitor subtle changes. Therefore, selecting an appropriate flight altitude and spatial resolution is crucial for optimizing vegetation monitoring effectiveness.

Construction and Evaluation of a Prediction Model for RCC

Measuring the RCC gives an idea of the growth status, nutritional status, and health of the plant. This is important for the timely detection of problems such as plant diseases, pests, or nutritional deficiencies, and by regularly monitoring chlorophyll content, farmers can take appropriate measures to protect plant health and improve crop yield and quality (*Zhao et al., 2023*). Through the use of tools such as remote sensing technology or portable chlorophyll meters, chlorophyll content can be monitored in real-time over large areas of farmland, allowing early detection of poor plant growth or disease problems. At the same time, based on trends in chlorophyll content, crop yields can be predicted and measures can be taken to improve yields and stabilize agricultural production.

The corresponding spatial resolution at this flight altitude is 0.017 m with the flying altitude of 35 m. At this spatial resolution, the optimal parameter combinations are obtained for each model as shown in Table 1.

Table 1

The parameter information of independent machine learning models at spatial resolution of 0.017 m of RCC

Model	Para1	Value1	Para2	Value2	Para3	Value3
Ridge	Alpha	100				
Lasso	Alpha	10	Max_iter	20		
SVM	C	0.1	Kernel	Linear		
MLP	Activation	Tanh	Hidden_layer_sizes	(25, 25, 25, 25)	solver	lbfgs
KNN	Algorithm	Kd_tree	Leaf_size	1	n_neighbors	9
RF	Min_samples_leaf	8	Min_samples_split	0.1	n_estimators	46
GBDT	learning_rate	0.01	Loss	ls	n_estimators	51

The above 7 basic models are used as the base model and the linear regression algorithm is used as the stacking meta-model. After synthesizing the above independent machine learning models and using the same input data to get the prediction results obtained by the stacking model, a 1:1 comparison graph is constructed after normalizing the stacking model prediction results with a total of 8 sets of prediction results and actual values such as the prediction results of the aforementioned independent models, and the specific results are shown in Figure 3.

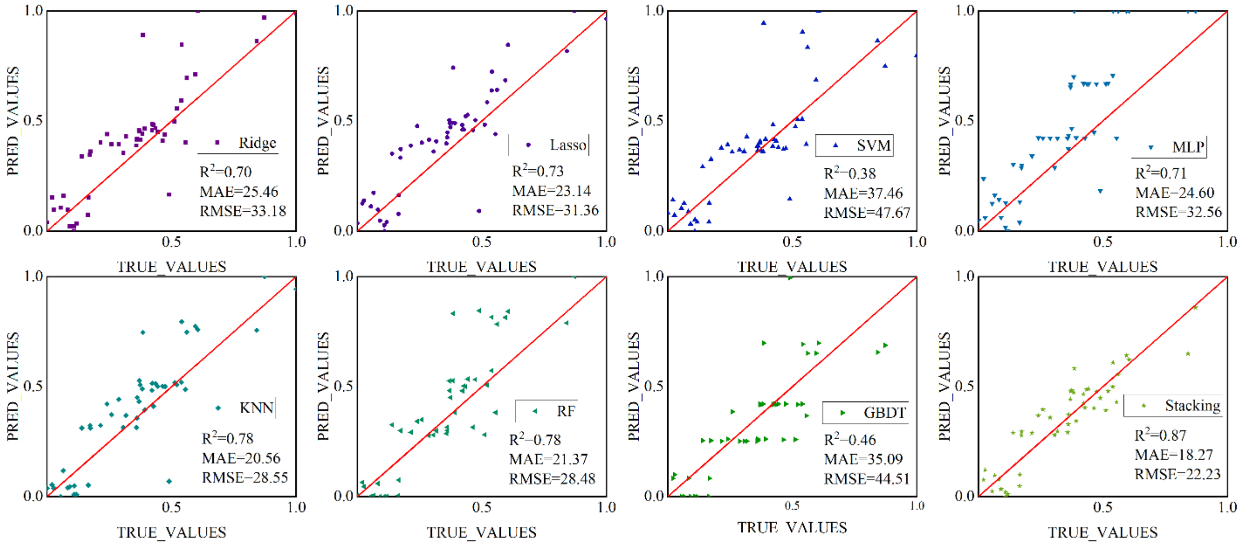

Fig. 3 - The plot of predicted versus measured values for eight models at spatial resolution of 0.017 m of RCC

At this spatial resolution, KNN and RF have the best prediction results among the seven independent machine learning models, with R^2=0.78, MAE=20.56, and RMSE=28.55 for KNN, and R^2=0.78, MAE=21.37, and RMSE=28.48 for RF. In contrast, the stacking model has R^2=0.87, MAE=18.27, and RMSE=22.23, and its three evaluation indices are better than the KNN and RF models. Hence, the prediction results of the stacking model are better than the seven independent models.

The corresponding spatial resolution at this flight altitude is 0.024 m with the flying altitude of 35 m. At this spatial resolution, the optimal parameter combinations are obtained for each model as shown in Table 2.

Table 2

The parameter information of independent machine learning models at spatial resolution of 0.024 m of RCC

Model	Para1	Value1	Para2	Value2	Para3	Value3
Ridge	Alpha	0.1				
Lasso	Alpha	0.001	Max_iter	210		
SVM	C	100	Kernel	Rbf		
MLP	Activation	Logistic	Hidden_layer_sizes	(50, 50)	solver	lbfgs
KNN	Algorithm	Kd_tree	Leaf_size	1	n_neighbors	4
RF	Min_samples_leaf	89	Min_samples_split	0.1	n_estimators	6

Model	Para1	Value1	Para2	Value2	Para3	Value3
Ridge	Alpha	0.1				
GBDT	learning_rate	0.1	Loss	lad	n_estimators	51

The above 7 basic models are used as the base model and the linear regression algorithm is used as the stacking meta-model. After synthesizing the above independent machine learning models and using the same input data to get the prediction results obtained by the stacking model, a 1:1 comparison graph is constructed after normalizing the stacking model prediction results with a total of 8 sets of prediction results and actual values such as the prediction results of the aforementioned independent models, and the specific results are shown in Figure 4.

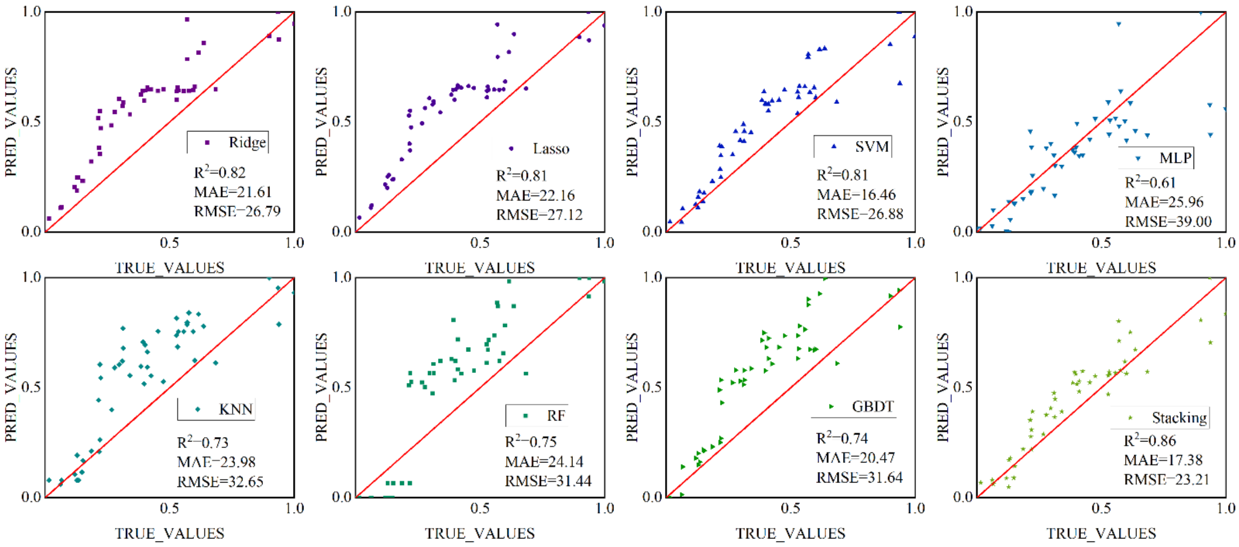

Fig. 4 - The plot of predicted versus measured values for eight models at spatial resolution of 0.024 m of RCC

At this spatial resolution, Ridge has the best prediction results among the seven independent machine learning models, with R^2=0.82, MAE=21.61, and RMSE=26.79; the stacking model has R^2=0.86, MAE=17.38, and RMSE=23.21, and all the evaluation metrics are better than Ridge model, so the stacking model's prediction results are better than seven independent models.

The corresponding spatial resolution at this flight altitude is 0.030 m with the flying altitude of 45 m. At this spatial resolution, the optimal parameter combinations is obtained for each model as shown in Table 3.

Table 3

The parameter information of independent machine learning models at spatial resolution of 0.030 m of RCC

Model	Para1	Value1	Para2	Value2	Para3	Value3
Ridge	Alpha	50				
Lasso	Alpha	10	Max_iter	10		
SVM	C	1	Kernel	Linear		
MLP	Activation	Tanh	Hidden_layer_sizes	(30, 30, 30)	solver	lbfgs
KNN	Algorithm	Kd_tree	Leaf_size	1	n_neighbors	9
RF	Min_samples_leaf	1	Min_samples_split	0.1	n_estimators	96
GBDT	learning_rate	0.1	Loss	lad	n_estimators	31

The above 7 basic models are used as the base model and the linear regression algorithm is used as the stacking meta-model. After synthesizing the above independent machine learning models and using the same input data to get the prediction results obtained by the stacking model, a 1:1 comparison graph is constructed after normalizing the stacking model prediction results with a total of 8 sets of prediction results and actual values such as the prediction results of the aforementioned independent models, and the results are shown in Figure 5.

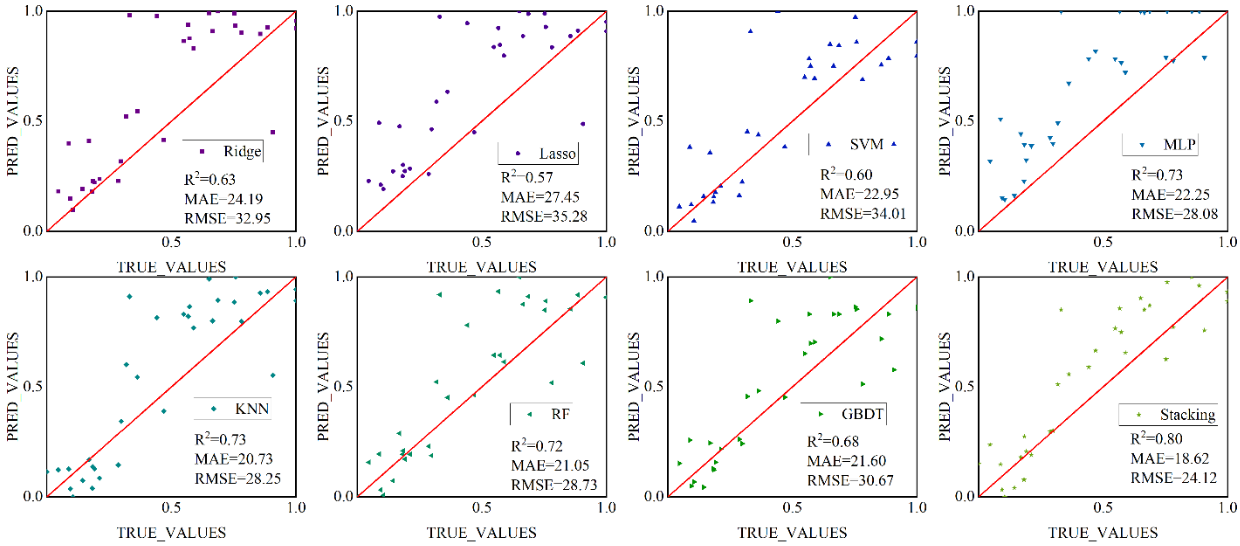

Fig. 5 - The plot of predicted versus measured values for eight models at spatial resolution of 0.030 m of RCC

At this spatial resolution, MLP and KNN have the best prediction results among the seven independent machine learning models, with R^2=0.73, MAE=22.25, and RMSE=28.08 for MLP, and R^2=0.73, MAE=21.05, and RMSE=28.73 for KNN. In contrast, the stacking model has R^2=0.80, MAE=18.62, and RMSE=24.12, and its three evaluation indices are better than the MLP and KNN models. Hence, the prediction results of the stacking model are better than the seven independent models.

When the spatial resolution is 0.017 m, the KNN and RF models have the best prediction results, however, the stacking model's prediction results are better than the seven independent models with R^2=0.87. When the spatial resolution is 0.024 m, the Ridge model has the best prediction results, and the stacking model's prediction results are better than the seven independent models with R^2=0.86. When the spatial resolution is 0.030 m, the MLP, and the KNN model have the best prediction, but the stacking model's prediction is still better than that of the seven independent models, with R^2=0.80.

Construction and Evaluation of a Prediction Model for LAI

The LAI is also an important indicator describing the vertical structure of vegetation, which reflects the amount of leaf area per unit surface area. By monitoring and analyzing changes in LAI, abnormal crop growth, malnutrition, or pest problems can be detected promptly and provide a scientific basis for agricultural management, such as fertilizer application, irrigation, and pest control, which can help to improve crop yield and quality, and LAI can be rapidly acquired and monitored by remote sensing technology, providing important information for land use, forestry resource management, water resource management, and so on *(Yamaguchi et al., 2023)*. The monitoring of LAI by remote sensing can realize the rapid assessment of vegetation growth status in large-scale areas and provide scientific support for decision-making on resource management and environmental protection.

When the UAV flight altitude is 25 m, the spatial resolution of multispectral is 0.017 m. In this spatial resolution, 11 target vegetation indices are taken as inputs to 7 independent machine learning algorithm models, the models are trained on the training set, and the validation set data is used to validate and evaluate the obtained models, and the optimal parameter combinations of each model are shown in Table 4.

Table 4

The parameter information of independent machine learning models at spatial resolution of 0.017 m of LAI

Model	Para1	Value1	Para2	Value2	Para3	Value3
Ridge	Alpha	0.1				
Lasso	Alpha	0.001	Max_iter	20		
SVM	C	5	Kernel	Linear		
MLP	Activation	Identity	Hidden_layer_sizes	(30, 30, 30)	solver	adam
KNN	Algorithm	Kd_tree	Leaf_size	1	n_neighbors	4
RF	Min_samples_leaf	3	Min_samples_split	0.3	n_estimators	11
GBDT	learning_rate	0.1	Loss	ls	n_estimators	46

The above 7 basic models are used as base models and the linear regression algorithm is used as a stacking meta-model. After synthesizing the above independent machine learning models and using the same input data to get the prediction results obtained by the stacking model, a 1:1 comparison graph is constructed after normalizing a total of 8 sets of prediction results with the actual values such as the prediction results of the stacking model and the prediction results of the aforementioned independent models, the specific results are shown in Figure 6.

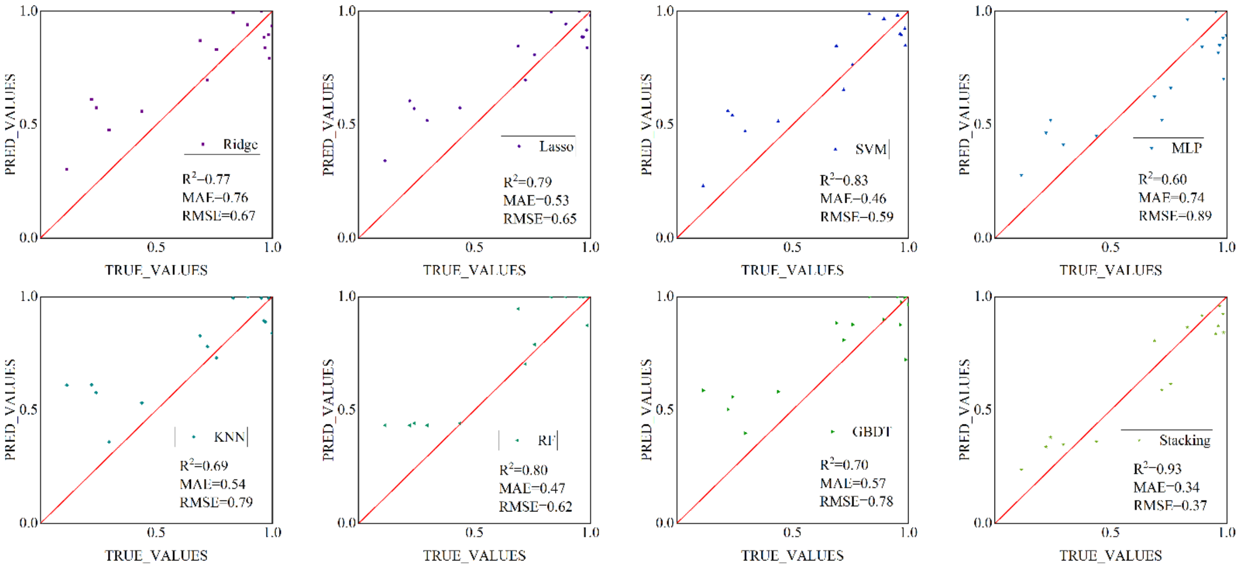

Fig. 6 - The predicted versus measured values for eight prediction models at spatial resolution of 0.017 m of LAI

At this spatial resolution, the best prediction among the seven independent machine learning models is the SVM model, which corresponds to R^2=0.83, MAE=0.46, and RMSE=0.59. The stacking model has R^2=0.93, MAE=0.34, and RMSE=0.37, and all the evaluation indices are better than those of the SVM model, so the stacking model's prediction results are better than seven independent models such as RF.

When the UAV flight altitude is 35 m, the spatial resolution of multispectral is 0.024 m. In this spatial resolution, The optimal parameter combinations for each model obtained at this spatial resolution are shown in Table 5.

Table 5

The parameter information of independent machine learning models at spatial resolution of 0.024 m of LAI

Model	Para1	Value1	Para2	Value2	Para3	Value3
Ridge	Alpha	50				
Lasso	Alpha	0.5	Max_iter	50		
SVM	C	10	Kernel	Rbf		
MLP	Activation	Relu	Hidden_layer_sizes	(25, 25, 25, 25)	solver	lbfgs
KNN	Algorithm	Kd_tree	Leaf_size	1	n_neighbors	1
RF	Min_samples_leaf	1	Min_samples_split	0.1	n_estimators	6
GBDT	learning_rate	1	Loss	lad	n_estimators	6

Then the above 7 basic models are used as the base model and the linear regression algorithm is used as the stacking meta-model. After synthesizing the above independent machine learning models and using the same input data to get the prediction results obtained by the stacking model, a 1:1 comparison graph is constructed after normalizing the stacking model prediction results with a total of 8 sets of prediction results and actual values such as the prediction results of the aforementioned independent models, and the results are shown in Figure 7.

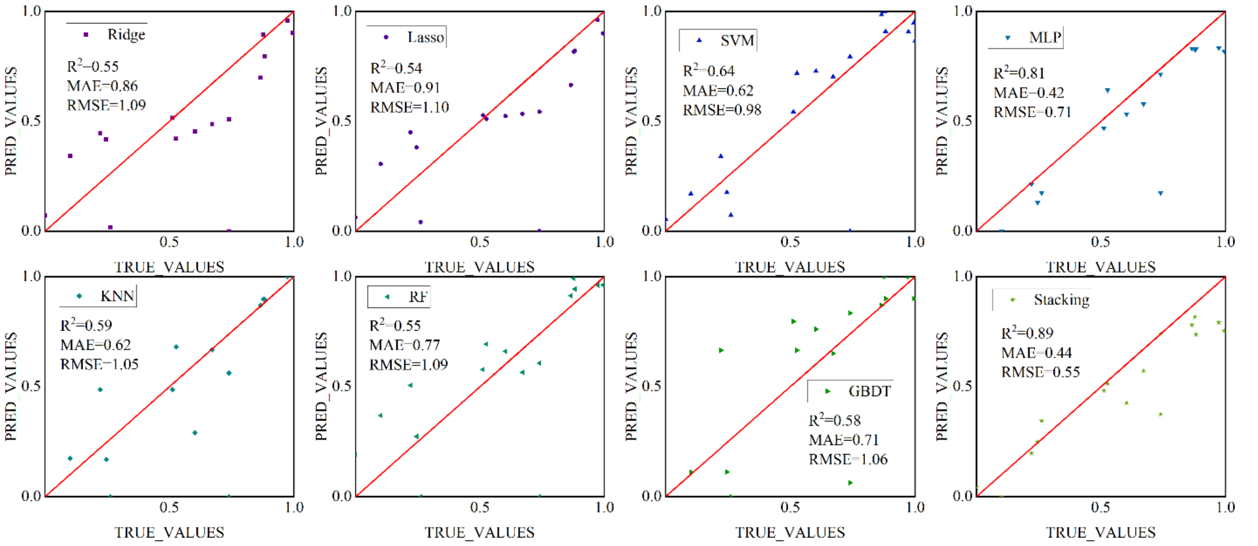

Fig. 7 - The predicted versus measured values for eight prediction models at spatial resolution of 0.024 m of LAI

At this spatial resolution, MLP has the best prediction results among the seven independent machine learning models, with R^2=0.81, MAE=0.42, and RMSE=0.71, the stacking model has R^2=0.89, MAE=0.44, and RMSE=0.55, and all the evaluation metrics are superior to those of the MLP model so that the stacking model's prediction results were better than seven independent models such as MLP.

When the spatial resolution is 0.017 m, the SVM model has the best prediction effect, but the stacking model has better prediction results than the seven independent models such as SVM, with R^2=0.93. When the spatial resolution is 0.024 m, the MLP model has the best prediction effect, and the stacking model still has better prediction results than the seven independent models such as MLP, with R^2=0.89. Unfortunately, not enough valid data were collected on the LAI of sorghum due to insufficient time at the spatial resolution of 0.030 m.

It was found that the models constructed at higher spatial resolution have higher R^2 values, lower MAE values, and lower RMSE values, indicating that increasing the resolution can improve the prediction accuracy of the models to some extent. Therefore, when conditions permit, lower flight altitude is considered to obtain higher spatial resolution and effectively improve the prediction model of RCC and LAI. Of course, the lower flight altitude, for a given monitoring area, represents the need to pay more monitoring time and slower monitoring speed, which needs to be measured according to the actual situation and trade-offs.

CONCLUSIONS

In previous studies, vegetation indices such as NDVI and EVI vegetation indices are mainly used to monitor crops in RCC and LAI prediction model *(Tian & Min, 1998)*. Linear regression models or simple nonlinear regression models with simple spectral indices are usually used to monitor crop growth *(Berger et al., 2020)*. However, because the spectral index varies greatly at different growth stages of crops, the monitoring accuracy and adaptability of the traditional methods need to be improved *(Ramsanthosh et al., 2021)*. Instead, this study used the vegetation index of plants, coupled with a stacked learning model, to go about exploring the optimal sorghum RCC and LAI prediction model at different spatial resolutions. Compared with the traditional, single machine learning model-based prediction method, the prediction model constructed based on integrated learning and using the stacking approach has higher prediction accuracy and better prediction results, to realize the rapid monitoring and prediction of sorghum growth in field environments *(Ashcraft & Karra, 2021; Yahata et al., 2017)*.

Although the prediction model constructed by combining the vegetation index with independent machine learning at different spatial resolutions can achieve high prediction accuracy, there are still some shortcomings in predicting and monitoring the values of RCC and LAI of sorghum. One of the challenges is that lower resolution results in a smaller amount of data obtained, as it requires less time to monitor the same area. This reduction in data volume affects both model construction and validation. Additionally, the parameter optimization method using grid search in this study is not sufficient, and a more dynamic update-based parameter optimization algorithm will be explored in future work. Furthermore, the unstable and unstructured environment of field crop survival, combined with the manual methods used to collect plant data, introduces a degree of subjectivity in data collection.

The study is also limited to a single species, with discontinuous observation times and a relatively small total sample size. These factors indicate that generalizing the conclusions of this study requires further exploration, testing, and research.

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