Inversion modeling of rice canopy nitrogen content based on MPA-GA-ELM UAV hyperspectral remote sensing

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Abstract: Nitrogen content is an important indicator to characterize the growth status of rice. UAV hyperspectral remote sensing technology was used to obtain the nitrogen content of rice canopy at regional scale in a timely manner. To improve the accuracy of high-spectral inversion of rice canopy nitrogen content, the marine predators algorithm (MPA) was used to downscale the hyperspectral information in the range of 400 nm to 1000 nm by using the UAV hyperspectral image data and the synchronously measured rice canopy nitrogen content as the data source, from which the hyperspectral characteristic variables for rice nitrogen content inversion modelling were extracted. And using the dimensionality reduction variables as the data base, two neural network inversion methods, including extreme learning machines (ELM), genetic algorithm optimization for extreme learning machines (GA-ELM), were used to establish the rice nitrogen content drone hyperspectral remote sensing inversion model, and the results showed that: (1) The hyperspectral range from 400 nm to 1000 nm was dimensionally reduced by MPA, and finally the continuous hyperspectral reflectance information was dimensionally reduced to four discrete hyperspectral feature wavelengths, 570, 723, 811 and 987 nm for subsequent inversion modeling of rice nitrogen content. (2) In the models adopted in this study, MPA-GA-ELM has the highest accuracy, where the R^2 of training data, the R^2 of test data, the RMSE of training data, and the RMSE of test data were 07984, 0.7357, 0.4615, 0.4878, respectively. This study provides data support and application basis for inverse UAV remote sensing diagnosis of nitrogen content in rice.
Keywords: UAV, Nitrogen inversion, rice, MPA, ELM, hyperspectral image
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1 Introduction

Rice is one of the important staple crops in China, among which rice grown in the northeastern regions of Liaoning, Jilin, and Heilongjiang is cold-land rice[1]. Cold-land rice is characterized by slow nutrient release due to low temperatures in early spring and low air and soil temperatures after rice transplanting. Therefore, a portion of chemical fertilizer supplementation is required during the critical fertility period of cold-land rice. Rice nitrogen content directly affects leaf color, which is the most direct kind of indicator of rice nutritional status. During cold-land rice production, agricultural producers mostly assess whether rice is deficient in nitrogen nutrients by observing changes in leaf color on site, and then make field management decisions[2]. As land transfer in northeast China continues to deepen and cold rice production continues to expand, there is an increasing demand for intelligent management of rice production, and there is an urgent need to use information technology to conduct high-throughput, nondestructive, and accurate detection of cold rice nitrogen content, to assist in accurate decision-making in rice nutrition diagnosis, and to enhance the digitalization of the cold rice production process on a large scale[3].

Existing studies have shown that changes in nitrogen content of rice cause changes in reflectance at the spectral level in different bands. Due to the high data dimensionality of hyperspectral information, it is usually necessary to downscale the hyperspectral data before further establishing a quantitative inversion model with nitrogen content. Researchers at home and abroad have made some research results in estimating the nitrogen content of crops using hyperspectral techniques[4,5].

In recent years, a great deal of research has been carried out in China and abroad on the rapid and non-destructive monitoring of the nitrogen content of crop leaves by hyperspectral means, both in dried and fresh leaves. Some research on inversion models of crop nitrogen status, mainly focusing on leaf nitrogen content, leaf nitrogen accumulation and aboveground nitrogen accumulation of crops. Xue[6] showed that the correlation between leaf nitrogen accumulation and canopy hyperspectral reflectance was consistent over the entire fertility period, and the predictive ability of the model for estimating leaf nitrogen accumulation was better; Zhao[7] showed that the response of rice leaf nitrogen accumulation to canopy spectral parameters was more sensitive than that of leaf nitrogen. Kokaly[8] used an infrared spectrometer (NIR Spectrometer) to detect the reflectance spectra of dried leaf powder and transformed the reflectance spectra (R) with parameters such as 1/R, log (1/R), derivative spectra (KR) and regression analysis with the corresponding nitrogen content data, resulting in nitrogen sensitive bands, and finally a regression model for nitrogen content was developed. Tian[9], comprehensively analyses the quantitative relationship between the hyperspectral vegetation index of rice canopy and leaf nitrogen concentration, and the results showed that the three blue light bands showed a highly significant linear correlation with the leaf nitrogen concentration of

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rice, and this vegetation index had a good predictive property for the leaf nitrogen concentration of rice. Artificial neural networks are learning, fault-tolerant and real-time, and have unparalleled advantages for fitting non-linear problems, providing effective technical and theoretical support in many fields. Research on artificial neural networks for hyperspectral inversion of crop nitrogen is also increasing. Using the nitrogen spectral sensitivity index as the input variable and the canopy nitrogen content data as the output variable, Li Xuqing[10] used the random forest algorithm to construct a hyperspectral inversion model for rice canopy nitrogen content, and the coefficient of determination R^2 reached above 0.81 with high model accuracy.

In order to improve the accuracy of hyperspectral remote sensing diagnosis and management decision basis of nitrogen content in cold rice, this study used a multi-rotor UAV hyperspectral remote sensing platform to obtain canopy hyperspectral information of rice at key fertility stages, and used the hyperspectral information feature band selection method to select specific feature bands from the obtained hyperspectral band range, and then used the extreme learning machine (ELM) method to establish an inverse model of rice nitrogen content. This study can provide an efficient, reliable, and accurate means of remote sensing monitoring technology for the detection and precise management of nitrogen content during large-scale rice production in the cold northeast China.

2 Materials and methods

2.1 Study area and design

The test site was located at the precision agriculture aerial research base of Shenyang Agricultural University, Gengzhuang Town, Haicheng City, Liaoning Province (40°58'45.39"N, 122°43'47.0064"E), and the test variety was "Japonica 653", a variety widely grown in Liaoning. The experiment was conducted from June to September 2020, and the hyperspectral reflectance measurements and total nitrogen content of rice leaves were measured at the greening, tillering, nodulation and tasseling stages.

The experimental plots were designed with five N fertilizer gradient treatments (Figure 1), N0, N1, N2, N3, and N4, respectively; the plots were separated from each other by field ridges. N0 was the control group, i.e., no basal fertilizer was applied; N3 was the local standard N basal fertilizer application level with 150 kg/hm^2, N1 and N2 were the low N fertilizer application levels with 50 kg/hm^2 and 100 kg/hm^2, respectively; N4 was the high N fertilizer application level with 200 kg/hm^2; phosphorus and potassium fertilizers were applied according to the local standard application level. Each N fertilizer gradient was replicated three times, and each plot was 40 m^2 (5 m×8 m), with randomized groups. Nitrogen fertilizer was applied as base fertilizer: tiller fertilizer: spike fertilizer = 5:3:2. Other field management was carried out according to the local normal level. Samples were collected once a week, and four samples were taken from each plot to measure fresh matter weight, dry matter weight and nitrogen content.

2.2 UAV hyperspectral remote sensing image acquisition

The UAV hyperspectral platform adopts the M600 PRO six-rotor UAV from DJI Co., Ltd. and the hyperspectral sensor uses the GaiaSky-mini that a built-in push-scan airborne hyper-spectral imaging system from Sichuan Shuang li Hepu Company (Sichuan, China). The hyperspectral band range is 400-1000 nm, the resolution is 3.5 nm, and the number of effective bands is 170.

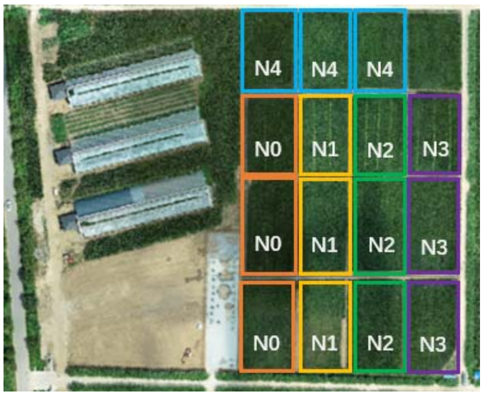


Figure 1 Test site of this study

The data acquisition time of hyperspectral remote sensing platform of UAV is between 10:00-11:00 a.m. in each test. During each flight, the period with relatively stable solar light intensity was selected, and the flight height of UAV is 150 m. In this study, the DN value of rice canopy was transformed into the hyperspectral reflectance information of rice canopy by field calibration. A black and white calibration blanket was placed on the path in the rice field. The hyperspectral information of the calibration blanket is included in the hyperspectral image collected by the UAV during the hyperspectral acquisition process. The DN value is converted into the spectral reflectance by formula (1).

$$\rho_t = \frac{DN_t - DN_1}{DN_2 - DN_1}(\rho_2 - \rho_1) + \rho_1 \tag{1}$$

where, ρ_t and DN_t are the reflectance and DN values of the ground object to be converted, and the reflectance of the calibration blanket are ρ_1 and ρ_2, respectively; DN_1 and DN_2 are the DN values of the calibration blanket.

We used the ENVI5.4 software to extract the hyperspectral data of the acquired hyperspectral remote sensing image, firstly using the K-means method is used for hyperspectral data classification. Since the rice field is mainly composed of rice, water, soil and other features, and taking into account factors such as classification errors, the number of categories is set at twice the number of major features and the maximum number of categories is set to 6 in this study. After that, the average spectrum of each area of interest was calculated as hyperspectral information for each test plot.

2.3 Measurement of nitrogen content

For each plot in the sampling point rice for the whole hole destructive sampling, brought back to the laboratory after the hole rice all fresh leaves cut off in the oven at 120°C to kill 60 min, and then dried at 80°C to constant weight. After weighing and crushing them, the ground powder was tested for nitrogen content (mg/g) of the leaves using the Kjeldahl method, as follows.

(1) Weighing and charring, put weighing paper in the analytical balance for zero calibration. The dried samples were put on the weighing paper and weighed 0.2±0.01 g. The weighed dried rice leaves were put into 50 mL conical flasks and numbered. 100 mL of concentrated sulfuric acid solution was added to the conical flasks, shaken well, and put into the drying vessel for 4 h until the samples in the flasks were completely charred.

(2) Boiling and distillation, add 2~3 mL of hydrogen peroxide solution with 30% concentration into each conical flask, then heat until acid mist appears, continue to heat for 10 min and remove, and continue to drop 2~3 mL of hydrogen peroxide solution with 30% concentration into it, heat until the solution in the flask is clear and transparent. Put the solution into a volumetric flask with a

range of 50 mL, let the solution cool down and fix the volume to 50 mL. Weigh 10 mL of boric acid solution with a concentration of 2% and add 1~2 drops of methyl red - bromocresol green indicator and place the configured boric acid solution at the outlet of the distiller. Measure 5 mL of the configured hydrogen peroxide solution mixed with 5 mL of 10 mol/L sodium peroxide solution and put it into the distiller for heating and distillation. At the same time, use pH test paper to test the pH of the condensate at the outlet of the distiller, and suspend the heating when the pH is equal to 7.

(3) Titration, the boric acid solution was titrated using sulfuric acid at a concentration of 0.02 mol/L until the boric acid solution gradually turned burgundy, and the volume of sulfuric acid used was noted. A blank control experiment was also conducted.

(4) Calculation of nitrogen content of rice leaves. The calculation formula was as follows.

$$\text{Nitrogen content (\%)} = \frac{(V_1 - V_0)\times N \times 0.014}{w}\times 100 \qquad (2)$$

where, V_1 and V_0 are the volume of sulfuric acid solution used for the sample and the volume of sulfuric acid solution used for the blank experiment, respectively; N is the concentration of sulfuric acid solution; w is the weight of the sample[11-13].

2.4 UAV hyperspectral feature band selection based on MPA

The full-band spectra acquired by the unmanned hyperspectral remote sensing system contain a large amount of redundant information unrelated to the nitrogen content of rice, which can lead to increased model error during inversion model building. Therefore, extracting useful information from the hyperspectral data is a prerequisite for building robust and accurate models. In this study, the marine predators algorithm (MPA) was used to extract hyperspectral information, which was then used as the input variable of the nitrogen content inversion model.

Marine Predators Algorithm (MPA) is a novel metaheuristic optimization algorithm proposed by Afshin Faramarzi et al. in 2020, which is inspired by the survival of the fittest theory in which marine predators choose the best foraging strategy between Lévy flight or Brownian motion. The MPA optimization process is described mathematically as follows:

(1) Initialization phase. Similar to most metaheuristics, MPA randomly initializes prey positions within the search space to initiate the optimization process. The mathematical description is described as follows:

$$X_0 = X_{\min} + rand(X_{\max} - X_{\min}) \qquad (3)$$

where, $X_{\max}$, $X_{\min}$ are the search space range; $rand(\ )$ is the random number within [0, 1].

(2) MPA optimization phase. At the beginning of the iteration, when the predator speed is faster than the prey speed the MPA, optimization process based on the exploration strategy is mathematically described as follows:

$$\begin{cases} stepsice_i = R_B \otimes (Elite_i - R_B \otimes Prey_i) \\ Prey_i = Prey_i + P\cdot R \otimes stepsice_i) \end{cases}$$

$$i = 1,2,...,n;\ Iter < \frac{1}{3}Max\_Iter \ \text{############}(4)$$

where, *stepsice* is the movement step; R_B is the Brownian wandering random vector with a normal distribution; $Elite_i$ is the elite matrix constructed from the top predators; $Prey_i$ is the prey matrix with the same dimension as the elite matrix; $\otimes$ is the term-by-term multiplicative operator; P is equal to 0.5; R is a uniform random vector within [0, 1]; n is the population size; *Iter*, *Max_Iter* are the current and maximum number of iterations, respectively.

In the middle of the iteration, when the predator and the prey are at the same speed, the prey is exploited based on the Lévy exploitation; the predator explores based on the Brownian roaming strategy and gradually shifts from an exploration to an exploitation strategy. The mathematical description of exploitation and exploration is as follows:

$$\begin{cases} stepsice_i = R_L \otimes (Elite_i - R_L \otimes Prey_i) \\ Prey_i = Prey_i + P\cdot CF \otimes stepsice_i) \end{cases}$$

$$i = 1,2,...,n/2;\ \frac{1}{3}Max\_Iter < Iter < \frac{2}{3}Max\_Iter \ \text{####}(5)$$

$$\begin{cases} stepsice_i = R_B \otimes (R_B \otimes Elite_i - Prey_i) \\ Prey_i = Elite_i + P\cdot CF \otimes stepsice_i) \end{cases}$$

$$i = n/2,...,n;\ \frac{1}{3}Max\_Iter < Iter < \frac{2}{3}Max\_Iter \ \text{#####}(6)$$

where, R_L is the random vector with Lévy distribution; $CF = (1 - Iter/Max\_Iter)^{(2-Iter/Max\_Iter)}$, is an adaptive parameter that controls the step size of the predator; the other parameters are the same as above.

At the end of the iteration, when the predator speed is slower than the prey speed, the predator uses an exploitation strategy based on Lévy wandering. The mathematical description is as follows:

$$\begin{cases} stepsice_i = R_L \otimes (R_L \otimes Elite_i - Prey_i) \\ Prey_i = Elite_i + P\cdot CF \otimes stepsice_i) \end{cases}$$

$$i = 1,2,...,n;\ Iter > \frac{2}{3}Max\_Iter \ \text{############}(7)$$

where the parameters have the same meaning as above.

(3) Fish aggregation devices (FADs) or eddy effects. This strategy allows the MPA to overcome early convergence problems in the search for an optimum,and escape from local extremes during the process of finding an optimum. It is mathematically described as follows:

$$Prey_i \begin{cases} Prey_i + CF[X_{\min} + R_L \otimes (X_{\max} - X_{\min})] \otimes Ur & r \le FADs \\ Prey_i + [FADs(1-r)+r](Prey_{r1} - Prey_{r2})r & r > FADs \end{cases} \text{#}(8)$$

where, $FADs$ are the influence probabilities, 0.2; U is a binary vector; r is a random number within [0, 1]; $r1$ and $r2$ are the random indices of the prey matrix, respectively[14-16].

2.5 GA-ELM inversion modeling of nitrogen content

In this study, the extreme learning machine (ELM) model based on genetic algorithm (GA) was used to retrieve the nitrogen content of rice canopy.The ELM has been widely used in many fields for its advantages such as fast learning speed and small training error. However, the algorithm randomly generates the connection weights of the input and implicit layer builds and the thresholds of the implicit layer neurons, and there is no need to adjust them during the training process, which leads to the poor stability and generalization ability of the inverse model built by this algorithm. In this study, a genetic algorithm based on the evolutionary theory of superiority and inferiority, natural selection, and survival of the fittest species genetic ideas is used to optimize the ELM. The specific implementation steps of the genetic algorithm optimization are as follows:

(1) An initial population $X_{m\times l}$ is randomly generated, where m is the initial population number, the individual length l represents both the number of gene values in each individual and the initial number of weights of a neural network, and the gene values in the

individuals correspond to the initial weights of the neural network. This study uses real number encoding for gene values, which can avoid the decoding process and improve the training efficiency.

$$l=s_1s_2+s_2s_3+s_2+s_3 \tag{9}$$

where, l is the length of the individual; s_1 is the number of nodes in the input layer; s_2 is the number of nodes in the hidden layer; s_3 is the number of nodes in the output layer.

(2) The genetic algorithm calculates the output error value E_i and the fitness value f_i for each individual in the initial population, and evaluates the size of the individual fitness value f_i, and selects the individual with the larger fitness value in the initial population to enter the sub-population for further optimization training.

$$f_i=\frac{1}{1+E_i} \tag{10}$$

In the subpopulation, the probability that the i-th individual is selected for crossover or mutation is p_i, and the crossover rate p_c and mutation rate p_m are used to determine whether the individual needs to be crossed over or genetically manipulated according to the adaptive function of the crossover rate p_c and mutation rate p_m. The values of p_c and p_m will change adaptively according to the size of the individual adaptation value f_i, which can avoid problems such as randomization of search, slow search speed, loss of important genes of antibodies and reduced chance of generating new individuals caused by too high or too low p_c and p_m, and keep the population always diverse.

$$p_i=f_i\Big/\sum_{i=1}^{m}f_i \tag{11}$$

$$p_c=\begin{cases}k_c(f_{\max}-f_c)/(f_{\max}-\bar{f}), & f_c\geq\bar{f}\\ k_c, & f_c<\bar{f}\end{cases} \tag{12}$$

$$p_m=\begin{cases}k_m(f_{\max}-f_m)/(f_{\max}-\bar{f}), & f_m\geq\bar{f}\\ k_m, & f_m<\bar{f}\end{cases} \tag{13}$$

where, k_c and k_m are real numbers less than 1; f_c is the individual fitness value to be crossed; f_m is the individual fitness value to be varied; $f_{\max}$ is the upper bound of the fitness value f_i, and $\bar{f}$ is the mean value of the fitness value f_i. The flow chart of ELM based on GA optimization is shown in Figure 2.

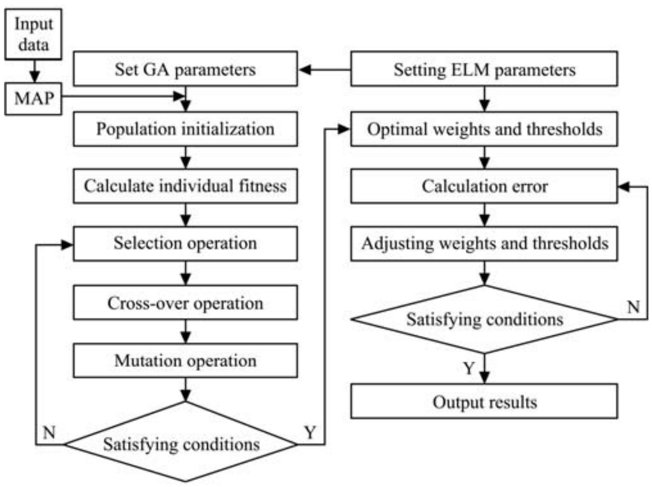


Figure 2 MPA-GA-ELM method

In this study, the RMSE and coefficient of determination (R^2) were used as evaluation criteria for assessing the accuracy of the UAV hyperspectral remote sensing inversion of rice canopy nitrogen content in cold area[17,18].

3 Results and discussion

3.1 Data processing

A total of 252 sets test data samples were collected in this study, and the samples were divided according to the 3:1 ratio of training set and validation set according to the Kennard-Stone algorithm, 190 of which were randomly selected as the modeling data set and the other 62 sets as the validation data set. The maximum nitrogen content of the sample set was 4.60 mg/g and the minimum nitrogen content was 1.02 mg/g, with a coefficient of variation of 0.33 (Table1).

Table 1 Statistical table of nitrogen content in rice leaves

Sample set	Samples	Minimum /mg·g^{-1}	Maximum /mg·g^{-1}	Mean /mg·g^{-1}	Coefficient of Variation
Whole	252	1.02	4.60	2.82	0.33
Training set	190	1.02	4.35	2.88	0.33
Validation set	62	1.14	4.60	2.76	0.32

3.2 Results of hyperspectral feature band selection

The reflectance spectral data from 400 to 1000 nm obtained from the test plots were smoothed using the Savitzky-Golay convolutional smoothing algorithm, and MPA was used to extract the feature bands for the inversion of rice nitrogen content in this study. Figure 3 shows the results of feature bands extracted by MPA algorithm for japonica rice canopy hyperspectral information, and the best feature bands are 570, 723, 811 and 987 nm.

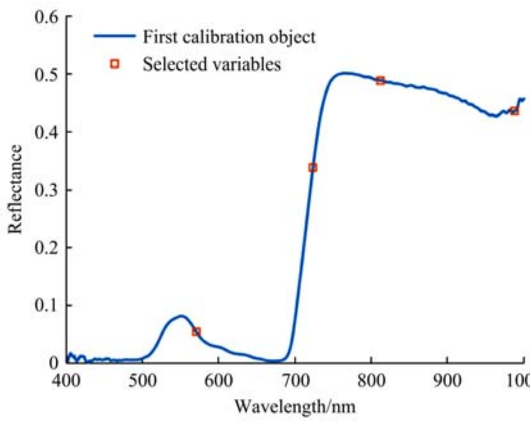


Figure 3 Hyperspectral feature wavelength

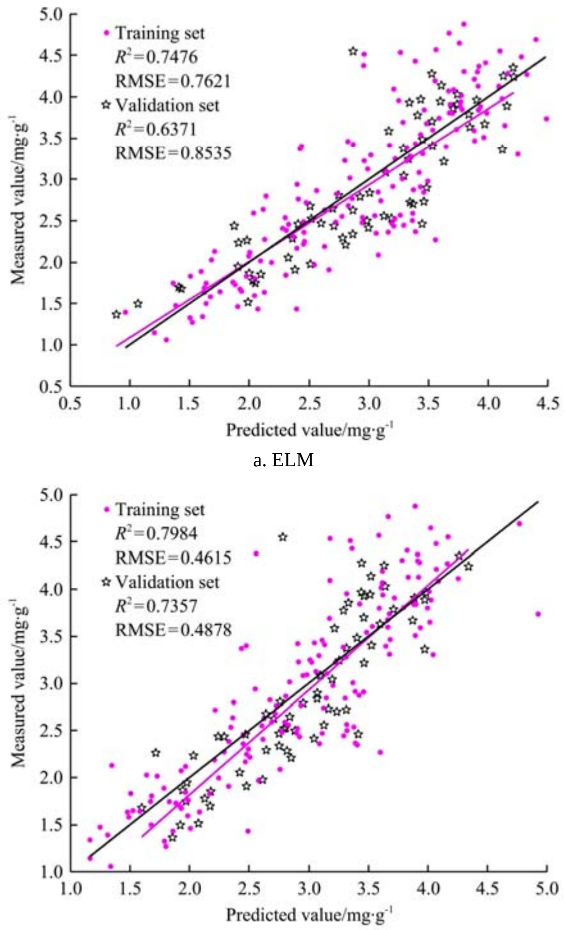
From Figure 3, the feature bands extracted in this study are mainly in the hyperspectral feature wavelength range such as green region, red edge position, and near infrared band.

3.3 Inversion results of GA-ELM for nitrogen content

In this study, extreme learning machines (ELM), genetic algorithm for extreme learning machines (GA-ELM), were used to develop an inversion model of rice nitrogen content using the results of MPA downscaling as input and rice nitrogen content as output.

The parameters of GA-ELM were determined after repeated tests: the activation function is Sigmoid, the output function is Purelin, the training function is trainlm, the crossover probability = 0.6, the variation probability = 0.3 the coefficient of determination R^2 and the root mean square error RMSE as the evaluation criteria of the model. The modeling results are shown in Figure 4.

As shown in Figure 4, among the inversion models of rice nitrogen content developed by the two modeling approaches, the GA-ELM model has better inversion than ELM, with R^2 above 0.7357 and RMSE below 0.4878 mg/g in both the training and validation sets (Table 2).



a. ELM

b. GA-ELM

Figure 4 Results of rice nitrogen content inversion

Table 2 Results of three modeling methods by ELM, GA-ELM

Methods	ELM	GA-ELM
R^2	0.7476 (train)	0.7984 (train)
	0.6371 (test)	0.7357 (test)
RMSE	0.7621 (train)	0.4615 (train)
	0.8538 (test)	0.4878 (test)

The model accuracy of the rice nitrogen content inversion model using the traditional limit learning machine algorithm is weaker than that of the rice nitrogen content inversion model using the genetic algorithm. This result is mainly due to the fact that the model parameters of the ELM alone are set at the time of modeling and lack the optimization process, i.e., it is not possible to determine whether the given parameters are optimal solutions. Instead, the parameters of the ELM model are continuously optimized iteratively through the multi-objective function optimization algorithm, with the error size between the calculated value and the true value as the measurement basis, and the ELM model parameters are determined by setting the error threshold, thus improving the accuracy of rice nitrogen content inversion.

3.5 Analysis of nitrogen content inversion model

In this study, we extracted the characteristic bands of hyperspectral information of japonica rice canopy acquired by UAV through MPA method, and established the inversion model of rice nitrogen content using GA-optimized extreme value learning machine algorithm to realize the rapid monitoring and evaluation of UAV remote sensing inversion of rice canopy nitrogen content in northern China. Since the MPA algorithm is inspired by the movement patterns of marine predators and prey. The predator and prey update their positions according to Lévy motion or Brownian motion in the process of seeking advantages, and at the same time, the prey acts as the predator identity while being predated, which makes the algorithm more dynamic, faster convergence speed and convergence accuracy. Therefore, in this paper, the mpa spectral signal dimension is compressed to reduce the number of feature bands, and four feature bands, 570, 723, 811 and 987 nm, are selected and used as the input of the rice nitrogen content inversion model. Since the traditional one- or multiple regression statistical models based on hyperspectral feature bands limit the accuracy of rice nitrogen content inversion to a certain extent, and cannot fully express the nonlinear mathematical relationship between spectral information and nitrogen content. Therefore, this paper adopts the artificial neural network-ELM, which has unparalleled advantages in fitting nonlinear problems, as the inversion model. The inverse modeling accuracy of GA-ELM was better than that of ELM, probably because the GA algorithm optimized the input weights and hidden layer thresholds of the extreme learning machine, which avoided the randomized input weights and hidden layer thresholds of ELM and the low number of hidden layer nodes. Given, the number of hidden layer nodes is small, the generalization ability is poor, and the calibration accuracy is low. In this study, the UAV hyperspectral remote sensing platform was used with certain acquisition errors, and the number of ground samples was still relatively limited due to the limitation of the UAV platform. The established nitrogen content inversion model was only established for the experimental rice varieties, and the applicability of this inversion method to other varieties of nitrogen content needs to be further improved. Therefore, in future studies, we will increase the number of experimental varieties and establish the inverse model of nitrogen content for different fertility stages of rice to improve the accuracy and generality of the model.

4 Conclusions

This paper is based on the hyperspectral remote sensing image data of rice unmanned aerial vehicle (UAV) in Shenyang, Liaoning, China, while using destructive sampling to obtain rice nitrogen content, and the hyperspectral remote sensing image is downscaled by the marine predators algorithm (MPA) to extract rice hyperspectral remote sensing features. On this basis, ELM, GA-ELM, were used to establish the hyperspectral remote sensing inversion model of rice nitrogen content, and the specific conclusions of this study are as follows:

(1) The hyperspectral range from 400 nm to 1000 nm was dimensionally reduced by MPA, and finally the continuous hyperspectral reflectance information was dimensionally reduced to four discrete hyperspectral feature wavelengths, 570, 723, 811 and 987 nm for subsequent inversion modeling of rice nitrogen content.

(2) In the models adopted in this study, MPA-GA-ELM has the highest accuracy, where the R^2 of training data, the R^2 of test data, the RMSE of training data, and the RMSE of test data were 07984, 0.7357, 0.4615, 0.4878, respectively.

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