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Estimation of Winter Wheat Chlorophyll Content Based on Wavelet Transform and the Optimal Spectral Index

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Abstract: Hyperspectral remote sensing technology plays a vital role in advancing modern precision agriculture due to its non-destructive and efficient nature. To achieve accurate monitoring of winter wheat chlorophyll content, this study utilized 68 sets of chlorophyll content data and hyperspectral measurements collected during the jointing stage of winter wheat over two consecutive years (2019–2020), under various fertilization types and nitrogen application levels. Continuous wavelet transform was applied to transform the original reflectance, ranging from 2^1 to 2^{10} , and the correlation matrix method was utilized to identify the spectral index at each scale, with the highest correlation to winter wheat chlorophyll content as the optimal spectral index combination input. Subsequently, winter wheat chlorophyll content prediction models were developed using three machine learning methods: random forest (RF), support vector machine (SVM), and a genetic algorithm-optimized backpropagation neural network (GA-BP). The results indicate that the spectral data processed through continuous wavelet transform at seven scales, from 2^1 to 2^7 , show the highest correlation with winter wheat chlorophyll content at a scale of 2^6 , with a correlation coefficient of 0.738, compared with the correlation of 0.611 of the original reflectance, and the accuracy is improved by 20.7%. The average highest correlation value between the spectral index at scale 2^6 and winter wheat chlorophyll content is 0.752. As the scale of wavelet transform increases, the correlation between the spectral index and winter wheat chlorophyll content and the accuracy of the predictive model show a trend of first increasing and then decreasing. The optimal input variables for predicting winter wheat chlorophyll content and the best machine learning method are the spectral data at a scale of 2^6 processing combined with the GA-BP model. The optimal predictive model has a validation set coefficient of determination (R^2) of 0.859, root mean square error (RMSE) of 1.366, and mean relative error (MRE) of 2.920%. The results show that the prediction model can provide a technical basis for improving the hyperspectral inversion accuracy of winter wheat chlorophyll and modern precision agriculture.

Keywords: winter wheat; chlorophyll content; hyperspectral; wavelet transform; optimal spectral index



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1. Introduction

As an important food crop in China, the planting area and yield of winter wheat play a central role in China [1]. However, the planting technology of winter wheat in some areas is relatively lagging behind, and this lack of modern planting management technology and equipment affects the yield and quality [2]. Therefore, it is of great strategic significance to strengthen the quality of domestic wheat planting and increase the yield to ensure national food security [3].

Chlorophyll is one of the most important pigments in plants; in the process of photosynthesis, chlorophyll plays a crucial role in facilitating energy conversion and sustaining the growth and development of plants. Furthermore, it acts as a protective and regulatory agent in maintaining plant health, thereby aiding in plant adaptation to external environmental conditions [4]. Romina et al. [5] used different kinds of chlorophyll instruments to determine the nitrogen content in crops by measuring the chlorophyll content of sweet peppers. Warlles et al. [6] utilized a portable chlorophyll meter for measuring the chlorophyll content in sorghum leaves; a significant correlation between photosynthetic pigments extracted in DMSO and leaf nitrogen content was determined. The above studies have indicated that chlorophyll content can be used to predict crop nitrogen requirements, assess crop photosynthetic capacity, and determine nutritional levels [7]. Accurate monitoring of the chlorophyll content in winter wheat can help prevent soil and water pollution caused by excessive fertilization [8]. The traditional method of measuring chlorophyll content involves sampling in the field and conducting measurements in indoor laboratories [9]. This method is not only time-consuming and labor-intensive, but also yields delayed and unstable results, greatly limiting the accuracy and timeliness of agricultural decision making [10]. In modern precision agriculture, efficient and non-destructive monitoring of crop growth status is vital [11]. Remote sensing technology, as a novel detection approach, enables the real-time acquisition of various spectral information of land cover on a large scale and has been widely applied in modern agricultural management [12].

With the advancement of hyperspectral remote sensing technology, leaf reflectance-based hyperspectral remote sensing is increasingly applied in the estimation of the chlorophyll content [13]. Currently, feature parameters selected based on maximum or local extreme values have been widely used as sensitive spectral variables for detecting the chlorophyll content [14]. Yoder et al. [15] found that the absorption, scattering, and transmission properties of chlorophyll in the visible light spectrum were more easily detectable and quantifiable. Saberioon et al. [16] estimated the chlorophyll content in the canopy layer at different growth stages using vegetation indices, achieving an estimation accuracy of R^2 up to 0.78. Yang et al. [17] separately utilized the Modified Soil Adjusted Vegetation Index 2 (MSAVI2) and spectral reflectance at 800 nm to establish chlorophyll content estimation models, with a modeling accuracy of R^2 reaching 0.88. However, during the dynamic growth period, effectively removing the interference signals, especially random and low-frequency signals, poses challenges and issues [18]. Previous studies have found that wavelet transform can effectively utilize hyperspectral reflectance data by preserving both global and local spectral information, facilitating a better analysis and interpretation of the data. Additionally, wavelet transform exhibits remarkable denoising capabilities as it can separate noise from signals at different scales or frequencies, effectively reducing the distortions caused by noise to enhance the accuracy of hyperspectral reflectance [19]. Liu et al. [20] used hyperspectral data, coupled continuous wavelet transform with the RF method, to construct a model for estimating the nitrogen content in summer corn, achieving remote sensing estimation of the nitrogen content and improving the modeling accuracy. Cheng et al. [21] studied continuous wavelet transform, utilizing spectral data from 265 leaf samples of 47 plants to effectively estimate the water content in the samples, with an accuracy as high as 75%. The aforementioned studies indicate that continuous wavelet transform can be utilized to enhance the modeling results for chlorophyll content detection.

Spectral indices are linear or nonlinear combinations of different sensitive bands, and compared with a single band, the hyperspectral vegetation indices constructed by screening bands based on the unique spectral characteristics of green vegetation contain more adequate crop growth information [22]. The correlation matrix method was used to select the optimal spectral bands with a high correlation to winter wheat chlorophyll content among all of the available bands [23]. Hyperspectral remote sensing technology has a finer division of spectra, which provides the possibility of selecting bands with a strong correlation with chlorophyll content in all of the available spectral bands for the construction of the optimal spectral index. The aim of this study is to investigate the correlation changes

of winter wheat chlorophyll content through the wavelet transformation of hyperspectral reflectance and spectral index selection. Subsequently, scales with poor correlation will be eliminated, and machine learning models will be employed to construct prediction models for the winter wheat chlorophyll content. The study will explore the impact of different scales and machine learning model combinations on the accuracy of chlorophyll content prediction, aiming to identify the optimal prediction model. Our goal is to propose a prediction model for monitoring the chlorophyll content during the growth process of winter wheat, providing a more precise and rapid scientific basis for the development of modern agriculture.

2. Materials and Methods

2.1. Overview of the Experimental Area and Experimental Design

This experiment was conducted in 2019 at the China Institute of Water-Saving Agriculture in Arid Areas, Northwest A&F University (34°17'44" N, 108°4'25" E). The study area is a typical dryland agricultural region in northwest China, characterized by a warm temperate monsoon semi-humid climate, with rainfall concentrated from July to September. The average annual precipitation is approximately 632 mm, with an evaporation of 1500 mm, and an average temperature of around 12.9 °C. The soil texture in the test area is heavy loam, the field water holding of the 0–100 cm section is 24%, and the withering water content is 8.5%. The pH of 0–20 cm sampled soil was 8.14, organic matter 12.0 g/kg, total nitrogen content 0.89 g/kg, total phosphorus 0.60 g/kg, total potassium 14.10 g/kg, alkaline nitrogen 55.3 mg/kg, effective phosphorus 8.21 mg/kg, and rapid potassium 132 mg/kg. Four N application levels were set up: N1: 100 kg/hm², N2: 160 kg/hm², N3: 220 kg/hm², and N4: 280 kg/hm². Four fertilizer types were set up: urea (U), slow-release fertilizers (SRF), UNS1 (ratio of U to SRF is 3/7), and UNS2 (ratio of U to SRF is 1/4). The experiments were conducted with no application of nitrogen fertilizer, and the control (CK) was used as a baseline. The experiment consisted of 17 treatments, each treatment was repeated three times, and the randomized block arrangement (positioning design) was adopted. The area of each plot was 7 m × 3 m = 21 m² and the sowing density was 180 kg/hm². There was a 2 m wide protected area around the experimental area and a 0.5 m wide isolation zone was set up between two adjacent plots. The experimental design was based on that of Tang et al. [24].

2.2. Data Acquisition

2.2.1. Remote Sensing Data Acquisition of Winter Wheat Canopy

This experiment was conducted on 31 March 2019 and 3 April 2020, respectively, using an ASD Field-Spec 3 back-mounted field spectrometer (Analytical Spectral Devices, Inc., Boulder, CO, USA). The weather was clear and windless with sufficient sunshine on the day of data measurement, and the measurement time was from 11:00 a.m. to 13:00 p.m. Three representative samples were selected for each plot, and nine spectral curves were collected from each sample at a time, and the average value was used as the spectral reflectance of the sample, with a total of 68 sets of data collected.

2.2.2. Winter Wheat Chlorophyll Content Acquisition

On the day of hyperspectral data collection, the winter wheat chlorophyll content data were acquired using the Soil and Plant Analyzer Development (SPAD-502, Inc., San Francisco, CA, USA) method. Prior to the measurements, the SPAD instrument was calibrated using leaf samples with a known chlorophyll content. The measurements were conducted on a clear, sunny day with ample sunlight. In order to minimize the sampling contingency, three random leaves were selected within each experimental plot for data collection, with their mean value serving as the measured value for each experimental plot.

2.3. Hyperspectral Data Preprocessing

2.3.1. SG Smoothing Processing

In order to reduce (eliminate) the impact of background noise, baseline drift, and stray light on the spectral reflectance curve, this study applied Savitzky–Golay convolution smoothing to the original spectral data in Origin 2023 (Origin Lab, Northampton, MA, USA). In order to effectively remove noise while maintaining the trend information in the data, a second-degree polynomial with nine smoothing points was used for function fitting and noise filtering [25].

2.3.2. Continuous Wavelet Transform

Wavelet transform is a mathematical tool used to analyze the local features of the signals, images, or data [26]. By convolving the signal with different scales and wavelet basis functions, we revealed the local features of the signal in time and frequency. Wavelet transform included Continuous Wavelet Transform (CWT) and Discrete Wavelet Transform (DWT), with CWT providing more shape and position information on the absorption features in vegetation spectra [27]. Meanwhile, within the scale range of 2^1 – 2^{10} , a sufficient level of resolution could be guaranteed to capture subtle variations in the signal, while also avoiding excessive refinement that may lead to noise amplification [28]. In this study, CWT was chosen, and the code was executed in MATLAB R2023a (Math Works Inc., Natick, MA, USA) to perform the wavelet transform and to obtain data at different transformation scales. The calculation formula is as follows:

$$\psi_{a,b}(\lambda) = \frac{1}{\sqrt{a}} \psi \frac{(\lambda - b)}{a} \quad (1)$$

$$W_f(a, b) = \int_{-\infty}^{+\infty} f(\lambda) \psi_{a,b}(\lambda) d\lambda \quad (2)$$

where $f(\lambda)$ is the crown height spectral reflectance, λ is the spectral band in the range of 350–1830 nm, $\psi_{a,b}(\lambda)$ is the wavelet basis function, a is scale factor, and b is the translation factor.

2.4. Selection and Construction of Spectral Index

To reduce noise and atmospheric interference and highlight specific spectral features, seven spectral indices, as shown in (Table 1), were selected. Among them, the relationships between RI and TVI with plant chlorophyll content and leaf area index were strong, but sensitivity decreased in the dense vegetation, mSR and mNDI optimized the specular reflectance effect of leaves and were more sensitive to leaf changes, DI, NDVI, and SAVI could reflect the background influences of the plant canopy and eliminate some errors [29].

Table 1. Selection of spectral indices.

Select Index	Computing Formula	Literature Number
Ratio vegetation index (RI)	R_i / R_j	[30]
Triangular vegetation index (TVI)	$0.5[120(R_i - R_{550}) / 200(R_j - R_{550})]$	[30]
Modified red edge simple ratio (mSR)	$(R_i - R_{455}) / (R_j - R_{455})$	[30]
Modified normalized difference index (mNDI)	$(R_i + R_j - 2R_{455}) / (R_i - R_j)$	[30]
Difference index (DI)	$(R_i - R_j)$	[30]
Soil-adjusted vegetation index (SAVI)	$(1 + 0.16) \frac{(R_i - R_j)}{(R_i + R_j + 0.16)}$	[30]
Normalized difference vegetation index (NDVI)	$(R_i - R_j) / (R_i + R_j)$	[30]

2.5. Model Construction

Based on the field experiments, a total of 68 samples of chlorophyll content and hyperspectral data of winter wheat canopy were collected. In this study, various optimal spectral index combinations were constructed as the input variables. Three machine learning methods, SVM, RF, and GA-BP, were employed for modeling the regression prediction of the chlorophyll content in winter wheat. After removing the outliers, two-thirds of the data were randomly selected as the training dataset and one-third as the validation dataset. The average of multiple predictions by the machine learning models was taken as the final model fitting result in this experiment.

2.5.1. RF

RF is an ensemble learning method that utilizes multiple decision trees to perform classification and regression tasks. In RF, each decision tree is trained on a random subset of the training dataset [31]. Moreover, for each decision tree, node splitting is also based on a randomly selected subset of features, thereby enhancing the model's generalization ability and reducing the risk of overfitting. During the training–testing process within the decision tree model, it is necessary to traverse each feature and method to effectively determine the optimal number of decision trees. After multiple rounds of training and error analysis, the number of decision trees in the RF model was determined to be 100.

RF derives the final prediction by averaging or voting on the predictions from each tree, thus effectively improving the accuracy and robustness of the model [32]. This model typically excels in handling large-scale datasets, high-dimensional features, and addressing missing data issues. RF models also offer good interpretability, providing feature importance rankings that aid in understanding the impact of different features on prediction outcomes.

2.5.2. SVM

SVM is a binary machine learning algorithm that utilizes Gaussian and polynomial kernels as the base kernel functions, and it optimizes the weight coefficients using the gradient descent algorithm [33]. It exhibits excellent generalization ability and robustness, without overfitting issues, and has been widely applied in pattern recognition, classification, and small-sample regression analysis [34]. Following the principle of minimizing the cross-validation error, the penalty coefficients C and γ of the SVM model in this study are set to 20 and 0.02, respectively.

2.5.3. GA-BP

GA-BP is a machine learning method that combines the genetic algorithm with the neural network. In traditional BP neural networks, the weights and bias parameters are updated by a gradient descent algorithm, but this leads to a weak model generalization ability due to the possibility of falling into problems such as local minima or overfitting.

To solve these problems, genetic algorithms can be introduced into BP neural networks to optimize the parameters of the neural networks for a better performance and generalization ability. The genetic algorithm is an optimization algorithm that simulates the process of biological evolution and searches for optimal solutions through operations such as selection, crossover, and mutation [35]. Combining the genetic algorithm with the BP neural network encodes the weights and bias parameters of the neural network as chromosomes, and these parameters are optimized by operations such as crossover and mutation of the genetic algorithm to obtain a better neural network model. By using BP neural networks optimized based on genetic algorithms, the performance and generalization ability of the model can be effectively improved, and the problem of falling into local optimal solutions can also be avoided.

2.6. Model Accuracy Validation

(1) Evaluation indicators

The model fitting results were evaluated using the root mean square error (RMSE), coefficient of determination (R^2), and the mean relative error (MRE)—the higher the R^2 , the higher the prediction accuracy of the model, and the smaller the RMSE and MRE, the more stable the prediction performance of the model and the more concentrated the prediction results [36].

(2) Significance analysis

By calculating the Pearson correlation coefficient and referring to the significance test table for correlation coefficients, for a sample size of 66, to achieve a highly significant correlation level ($p < 0.01$) and ensure the accuracy of estimating chlorophyll content, the correlation coefficient should exceed 0.310 [37].

3. Results

3.1. Correlation Analysis of Raw Hyperspectral Reflectance, Wavelet Transformed Hyperspectral Reflectance, and Chlorophyll Content

Using the Mexican hat wavelet function as the basis function for continuous wavelet transform (CWT), winter wheat hyperspectral data were decomposed to obtain the wavelet energy coefficients at different scales. To eliminate the influence of positive and negative correlations, the correlation coefficient was squared to calculate the determination coefficient (R^2). A noticeable improvement in the correlation between spectral data after partial-scale CWT transformation and chlorophyll content in winter wheat was observed compared with the original spectral reflectance data, as shown in Figure 1. Within small scales, a peak in correlation between the wavelet-transformed spectral reflectance and winter wheat chlorophyll content was observed near 750 nm. As the decomposition scale increased, the correlation between wavelet-transformed spectral reflectance and winter wheat chlorophyll content exhibited a trend of initially increasing and then decreasing. At a decomposition scale of 2^6 , the maximum correlation with chlorophyll content reached 0.738, representing an increase of 0.127 compared with the original spectral reflectance correlation of 0.611.

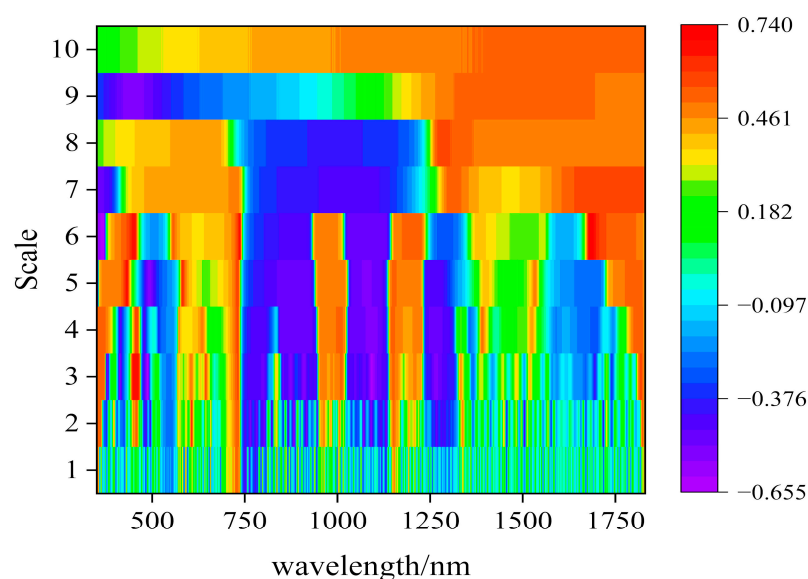


Figure 1. Correlation between wavelet transformed hyperspectral reflectance and chlorophyll content of winter wheat.

3.2. Construction of Spectral Indices and Extraction of Optimal Spectral Index Band Combinations

In order to more effectively utilize the information contained in the hyperspectral reflectance data, spectral indices were first calculated for each individual band of the hyperspectral reflectance data that had undergone CWT processing. Subsequently, a correlation analysis was conducted between these spectral indices and winter wheat chlorophyll content using the correlation matrix method. The bands with the highest correlation coefficients, *i* and *j*, were selected to construct different spectral indices. Seven spectral indices were then built, with the top five spectral indices showing the highest correlation with winter wheat chlorophyll content selected as the optimal spectral index combination. A correlation matrix plot was generated, as shown in Figures 2–4, where the color gradient from blue to red indicates the correlation between spectral indices and winter wheat chlorophyll content, ranging from negative to positive correlations. Figures 2–4 depict the correlation matrices between winter wheat chlorophyll content and hyperspectral vegetation indices obtained from wavelet transform at scales of 2^1 to 2^{10} . After undergoing continuous wavelet transform processing, the calculated optimal spectral indices showed a significantly higher correlation with winter wheat chlorophyll content compared with the original spectral data at certain scales. At the 26th scale, the average correlation coefficient between each optimal spectral index and winter wheat chlorophyll content was the highest at 0.752. The optimal spectral index combination at this scale included RI, DI, SAVI, NDVI, and mNDI. The optimal spectral index combinations for the rest of the transformed scales and the corresponding bands are shown in Table 2.

Table 2. Optimal spectral index band combinations at different transformation scales.

Transformation Scale	Spectral Index	Correlation Coefficient	Optimal Spectral Index Combination
0	RI	0.740	RI, DI, SAVI, NDVI, mNDI
	DI	0.865	
	SAVI	0.829	
	NDVI	0.731	
	TVI	0.134	
	mSR	0.368	
	mNDI	0.736	
2	RI	0.745	RI, DI, SAVI, NDVI, mNDI
	DI	0.686	
	SAVI	0.684	
	NDVI	0.719	
	TVI	0.587	
	mSR	0.490	
	mNDI	0.718	
4	RI	0.775	RI, DI, SAVI, NDVI, mNDI
	DI	0.765	
	SAVI	0.779	
	NDVI	0.738	
	TVI	0.587	
	mSR	0.458	
	mNDI	0.713	
8	RI	0.805	RI, DI, SAVI, NDVI, mNDI
	DI	0.817	
	SAVI	0.815	
	NDVI	0.774	
	TVI	0.543	
	mSR	0.299	
	mNDI	0.794	

Table 2. Cont.

Transformation Scale	Spectral Index	Correlation Coefficient	Optimal Spectral Index Combination
16	RI	0.744	RI, DI, SAVI, NDVI, mNDI
	DI	0.816	
	SAVI	0.841	
	NDVI	0.752	
	TVI	0.448	
	mSR	0.745	
	mNDI	0.793	
32	RI	0.764	RI, DI, SAVI, NDVI, mNDI
	DI	0.814	
	SAVI	0.845	
	NDVI	0.756	
	TVI	0.761	
	mSR	0.564	
	mNDI	0.759	
64	RI	0.750	RI, DI, SAVI, NDVI, mNDI
	DI	0.816	
	SAVI	0.842	
	NDVI	0.749	
	TVI	0.668	
	mSR	0.690	
	mNDI	0.749	
128	RI	0.715	RI, DI, SAVI, NDVI, mNDI
	DI	0.741	
	SAVI	0.755	
	NDVI	0.724	
	TVI	0.437	
	mSR	0.243	
	mNDI	0.703	
256	RI	0.716	RI, DI, SAVI, NDVI, mNDI
	DI	0.563	
	SAVI	0.731	
	NDVI	0.760	
	TVI	0.400	
	mSR	0.022	
	mNDI	0.744	
512	RI	0.758	RI, SAVI, NDVI, mSR, mNDI
	DI	0.571	
	SAVI	0.699	
	NDVI	0.759	
	TVI	0.124	
	mSR	0.674	
	mNDI	0.675	
1024	RI	0.659	RI, SAVI, NDVI, mSR, mNDI
	DI	0.607	
	SAVI	0.655	
	NDVI	0.658	
	TVI	0.526	
	mSR	0.690	
	mNDI	0.692	

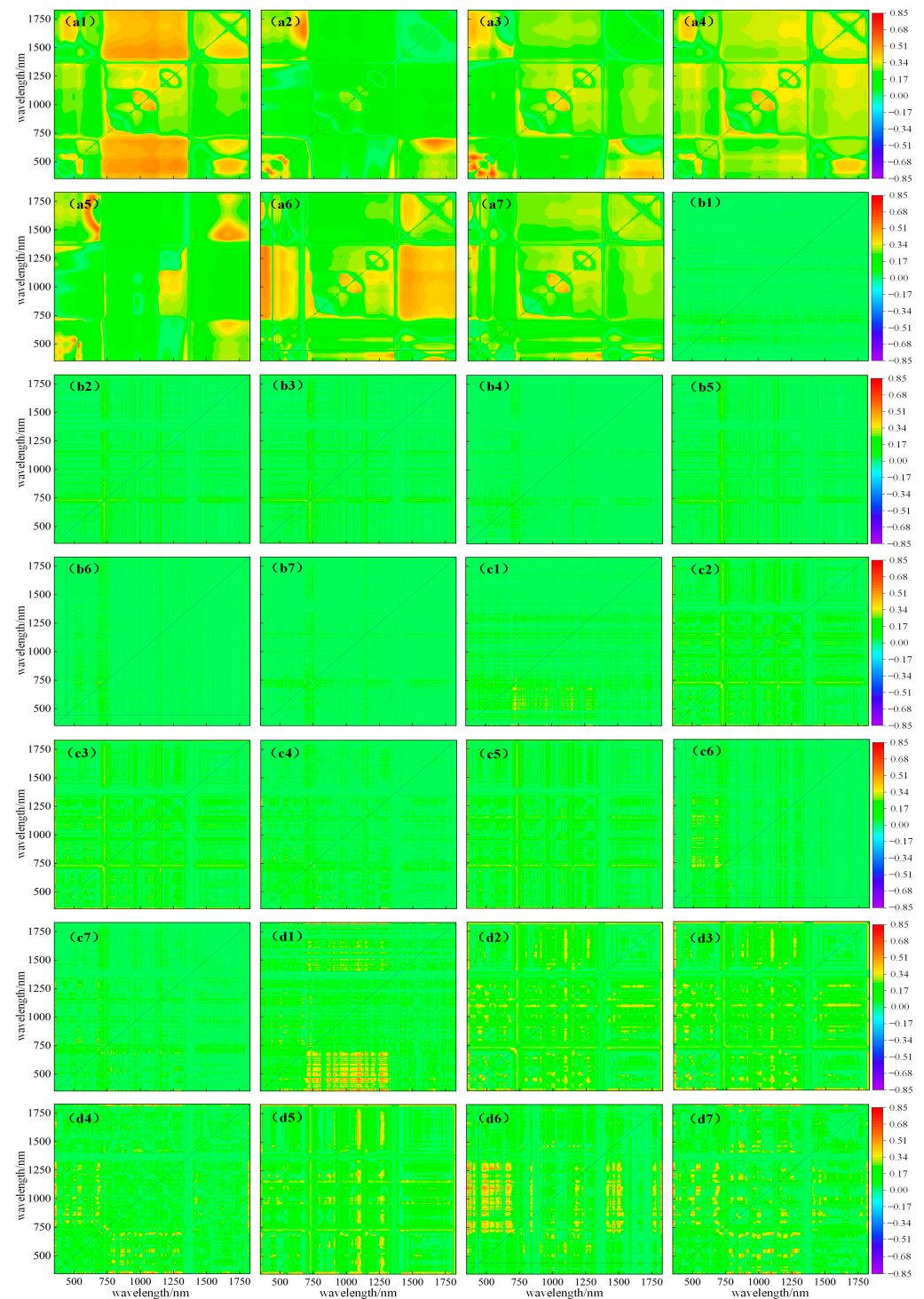


Figure 2. Correlation matrix of spectral indices at different scales: (a1–a7), (b1–b7), (c1–c7), (d1–d7) are the correlation of chlorophyll content screened by RI, DI, SAVI, NDVI, TVI, mSR, mNDI index of original reflectance at original scale, 2^1 transform scale, 2^2 transform scale and 2^3 transform scale.

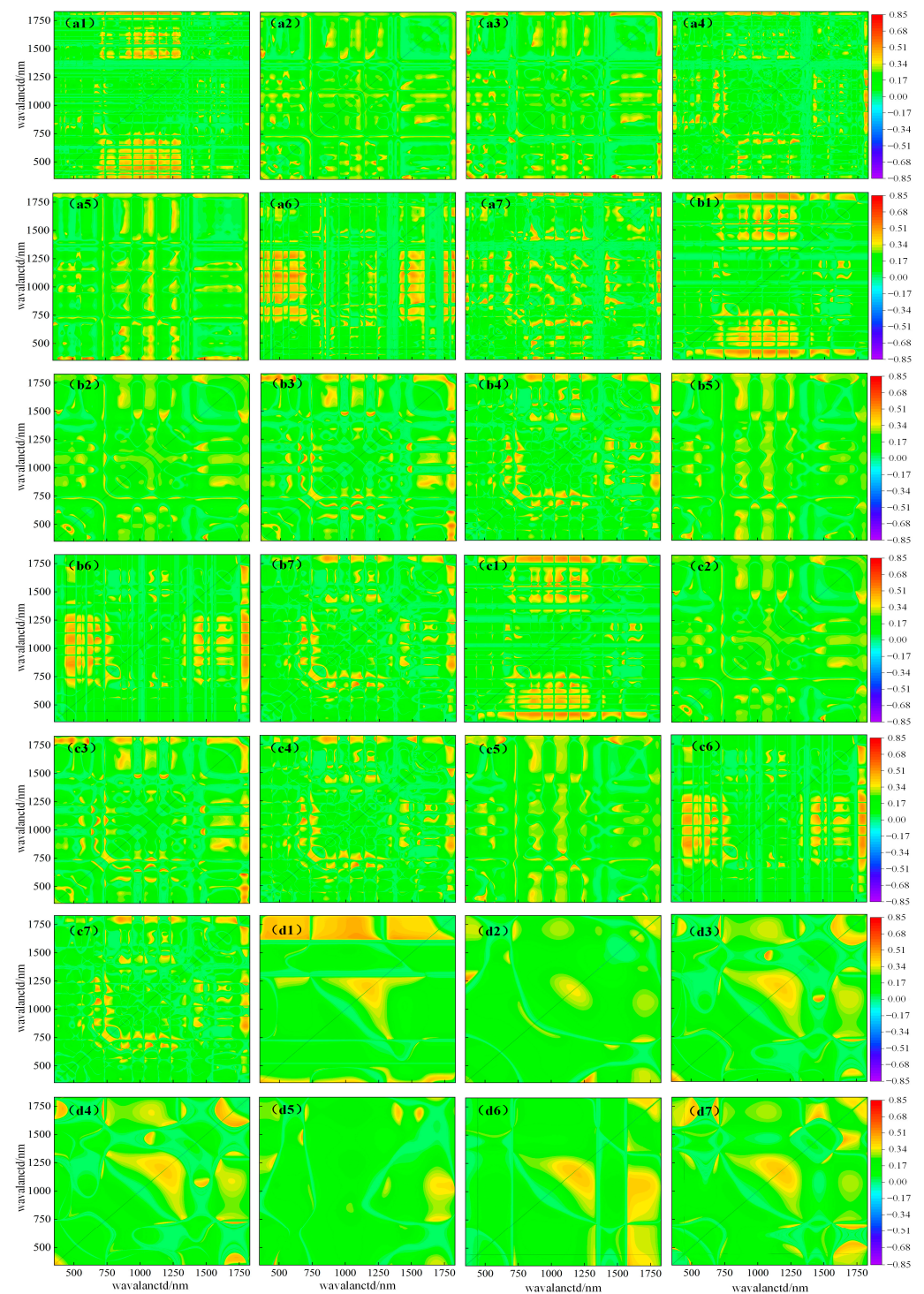


Figure 3. Correlation matrix of spectral indices at different scales: (a1–a7), (b1–b7), (c1–c7), (d1–d7) are the correlation of chlorophyll content screened by RI, DI, SAVI, NDVI, TVI, mSR, mNDI index of original reflectance at 2^4 transform scale, 2^5 transform scale, 2^6 transform scale and 2^7 transform scale.

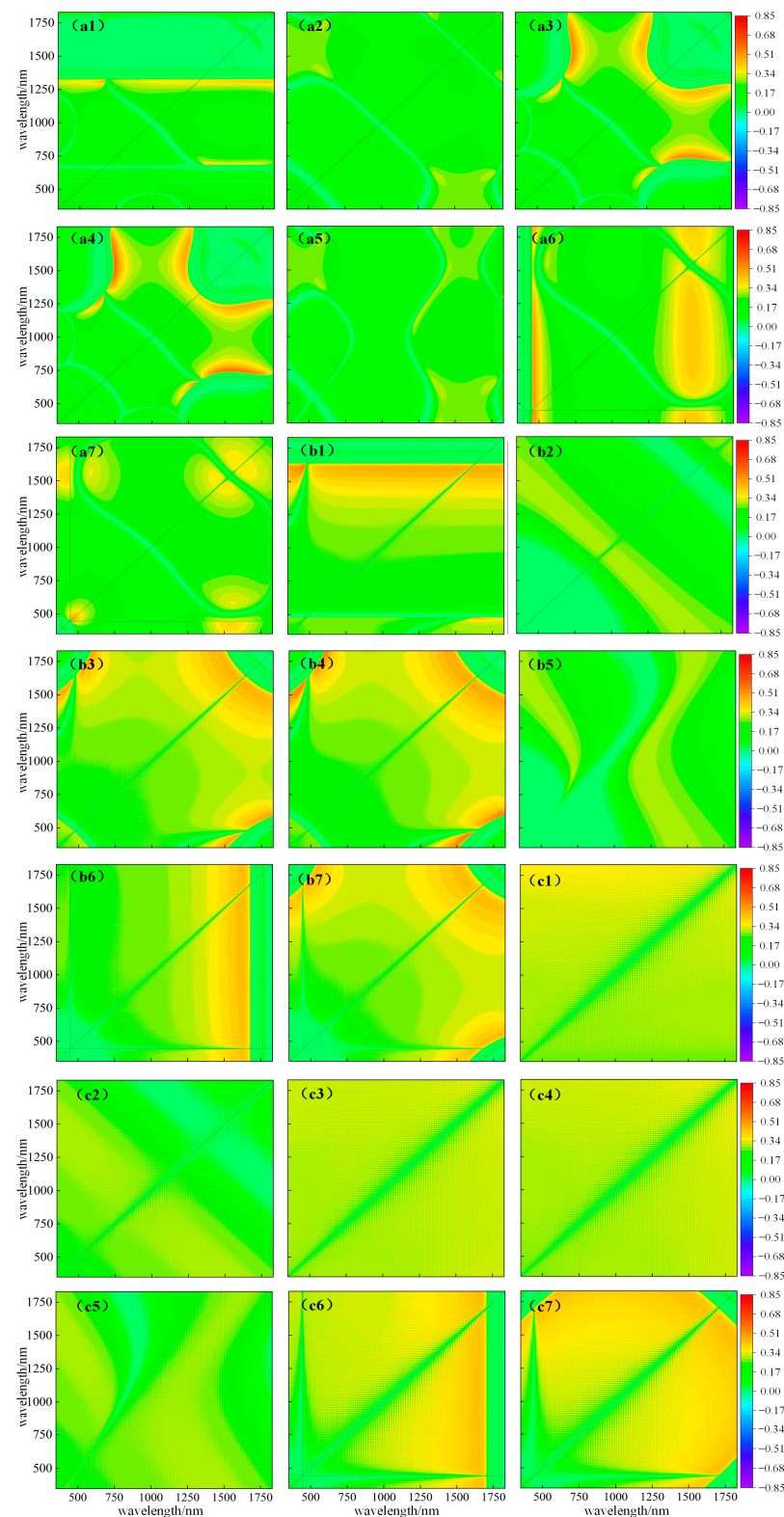


Figure 4. Correlation matrix of spectral indices at different scales: (a1–a7), (b1–b7), (c1–c7) are the correlation of chlorophyll content screened by RI, DI, SAVI, NDVI, TVI, mSR, mNDI index of original reflectance at 2^8 transform scale, 2^9 transform scale and 2^{10} transform scale.

3.3. Winter Wheat Chlorophyll Content Prediction Model Construction

With the increase in transformation scale, the correlation of spectral indices selected after 2^7 transformations continued to decrease. The correlation between spectral reflectance

transformed from 2^8 to 2^{10} and winter wheat chlorophyll content was lower than that of the original spectral reflectance. Therefore, high-scale transformations were excluded to select the optimal spectral index combination from scales 2^1 to 2^7 and winter wheat chlorophyll content as the model input variables. SVM, GA-BP, and RF models were used to construct the model estimating the winter wheat chlorophyll content, to comprehensively evaluate the accuracy of the model from the aspects of R^2 , RMSE, and MRE, respectively. R^2 , RMSE, and MRE aspects of the comprehensive evaluation of the model accuracy, different modeling combinations for winter wheat chlorophyll content prediction results are shown in Table 3 and Figures 5 and 6. The results showed that R^2 of the winter wheat chlorophyll content estimation model under different scales of continuous wavelet transform were 2^6 , 2^3 , 2^5 , 2^2 , 2^0 , 2^4 , and 2^7 in descending order; RMSE and MRE were 2^6 , 2^3 , 2^5 , 2^2 , 2^0 , 2^4 , and 2^7 in descending order; and RF, GA-BP, and SVM constructed by 2^6 -scale continuous wavelet transform spectral indices of winter wheat were used to predict the chlorophyll content of the model in the validation set. The validation set R^2 values of the chlorophyll content prediction model for winter wheat were 0.858 and 0.859, respectively, both higher than 0.310 ($p \leq 0.01$), indicating a highly significant correlation level with better linear fitting results. Under the same scale transform processing, the training set and validation set accuracies of the chlorophyll content prediction model of winter wheat constructed by the three modeling methods, from largest to the smallest, were GA-BP, RF and SVM. In summary, the 2^6 -scale continuous wavelet transform and GA-BP model were the optimal scale and the optimal model construction method in this study, and the modeling and validation sets of the optimal winter wheat chlorophyll content prediction model constructed from these models had R^2 of 0.858 and 0.859, RMSE of 1.281 and 1.366, and MRE of 2.621% and 2.920%, respectively.

Table 3. Model accuracy analysis.

Transformation Scale	Evaluation Indicators	GA-BP		RF		SVM	
		Training Set	Validation Set	Training Set	Validation Set	Training Set	Validation Set
0	R^2	0.686	0.667	0.659	0.641	0.635	0.626
	RMSE	2.430	2.401	2.524	2.406	2.841	2.685
	MRE/%	5.088	5.003	5.212	5.262	5.892	5.955
2	R^2	0.626	0.613	0.581	0.575	0.564	0.556
	RMSE	2.525	2.547	2.717	2.819	2.803	2.828
	MRE/%	5.470	5.274	5.719	6.089	5.887	6.273
4	R^2	0.691	0.690	0.671	0.659	0.654	0.562
	RMSE	2.101	2.028	2.327	2.381	2.532	2.583
	MRE/%	4.656	4.226	4.799	4.672	5.871	5.814
8	R^2	0.804	0.798	0.773	0.779	0.738	0.736
	RMSE	1.685	1.620	1.829	1.865	2.392	2.222
	MRE/%	3.402	3.540	3.959	3.969	5.039	5.038
16	R^2	0.661	0.656	0.630	0.621	0.619	0.610
	RMSE	2.729	2.836	2.789	2.837	3.257	3.363
	MRE/%	5.394	5.295	5.620	5.872	5.979	6.146
32	R^2	0.789	0.788	0.765	0.758	0.731	0.733
	RMSE	1.775	1.788	1.848	1.866	2.441	2.771
	MRE/%	3.659	3.670	3.689	4.169	5.321	5.276
64	R^2	0.858	0.859	0.803	0.809	0.777	0.779
	RMSE	1.281	1.366	1.563	1.663	1.808	1.978
	MRE/%	2.621	2.920	3.145	3.534	3.665	4.038
128	R^2	0.665	0.652	0.621	0.619	0.613	0.609
	RMSE	2.641	2.626	2.909	2.982	3.562	3.393
	MRE/%	5.923	5.873	6.155	6.212	6.853	7.271

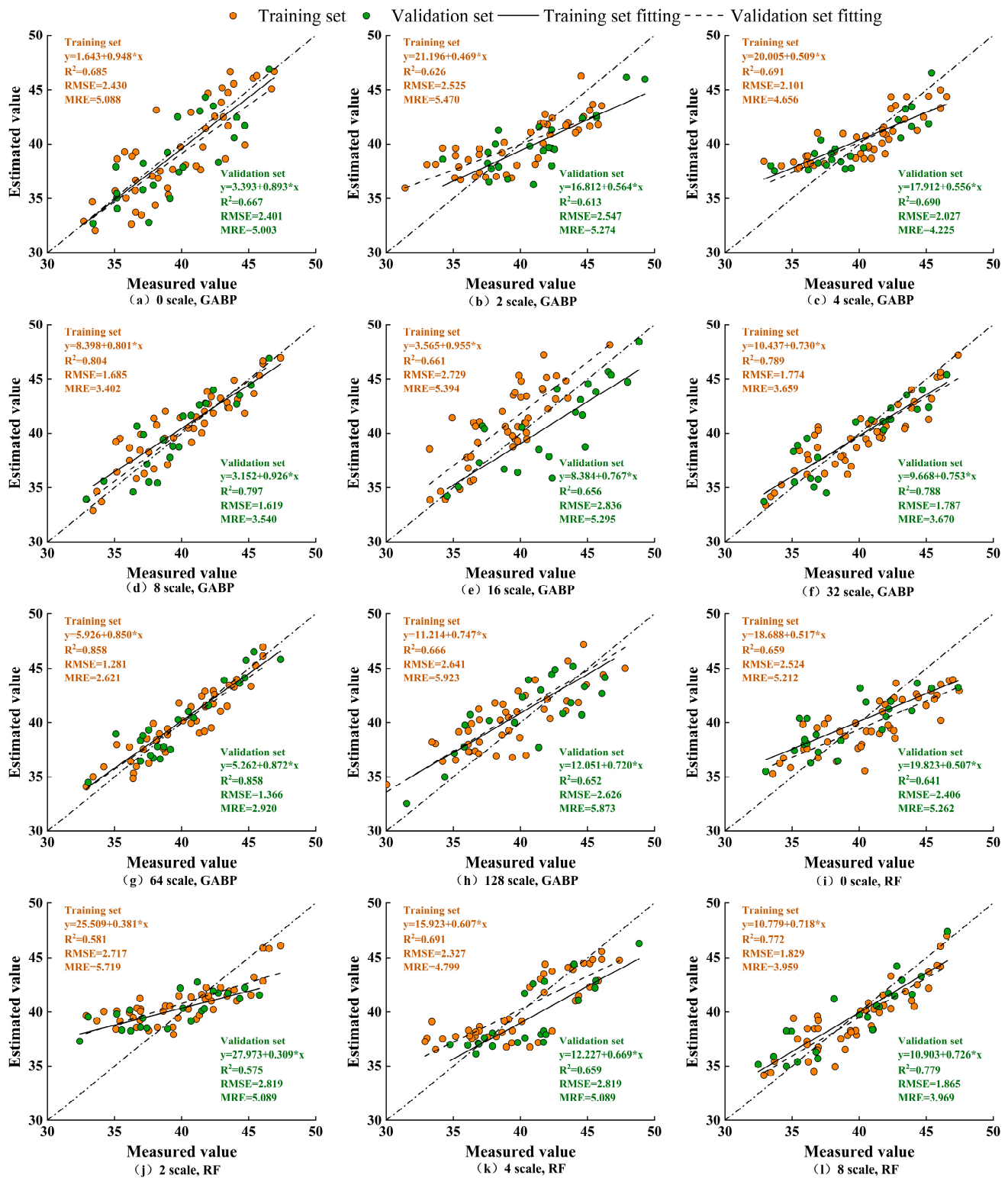


Figure 5. Modeling scatter plot. ((a–h) represents the GA-BP full-scale model, while (i–l) correspond to the original scale, 2¹-scale, 2²-scale, and 2³-scale RF models).

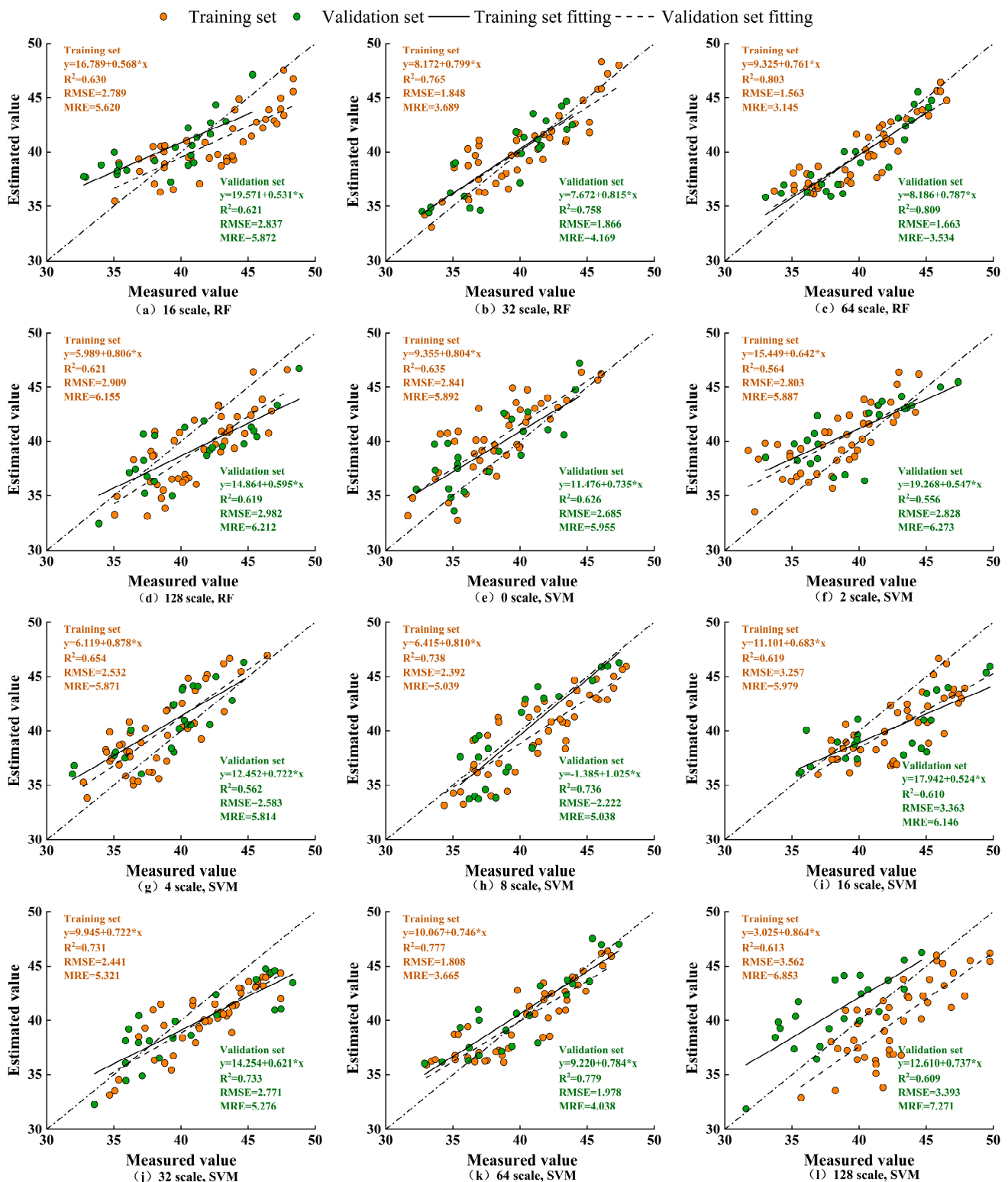


Figure 6. Modeling scatter plot. ((a–d) correspond to the 2^4 -scale, 2^5 -scale, 2^6 -scale, and 2^7 -scale RF models, while (e–l) represent the full-scale SVM model).

4. Discussion

Spectroscopic technology has shown great potential in monitoring crop growth and physiological indicators through Ahmad et al.'s research [38]. Among them, hyperspectral imaging, characterized by rich spectral information and strong band continuity, is com-

monly used for monitoring the crop chlorophyll content [39]. However, studies on the construction of chlorophyll content inversion models using hyperspectral reflectance have found that direct application of raw hyperspectral reflectance for chlorophyll content inversion modeling in crops can be affected by the soil background interference, atmospheric conditions, and lighting conditions; additionally, hyperspectral data contain a large number of bands, requiring extensive work and a high cost for direct application [40]. This is consistent with the research of Shu et al. [41], where the direct estimation of the chlorophyll content through hyperspectral remote sensing often exhibits poor model accuracy. For this reason, the introduction of continuous wavelet transform processing can decompose the hyperspectral data signals into frequency components of different scales, remove the noise in the data more easily, and at the same time identify the most informative features in the hyperspectral data, which can help simplify the dataset and improve the training efficiency and prediction accuracy of the model. In this study, the raw hyperspectral data were $2^1, 2^2, 2^3, \dots, 2^{10}$, ten scales of continuous wavelet transform, and we constructed an estimation model of chlorophyll content of winter wheat under the $2^1 \sim 2^7$ transform scales. With the improvement in the transform scales, the spectral index and chlorophyll content, as well as the model's accuracy, showed an increasing and then decreasing trend, and the optimal spectral index and chlorophyll content correlation under the 2^6 -scale transform and the accuracy of the estimation model constructed under the 2^6 -scale transform were higher than those in the other scales. This is consistent with the study by Li et al. [42], which found that the correlation coefficient was the highest at a scale of 6 using wavelet transform. This may be due to the fact that the continuous wavelet transform at small scales amplified subtle changes and noise, leading to loss or confusion of information; while at high scales, it may cause excessive smoothing, leading to loss of details. This situation may prevent the inversion model from accurately capturing the changes in chlorophyll content, thus reducing the accuracy of the model.

Wang et al. [43]'s research shows that the optimal spectral index constructed within the full spectral range contained a richer set of effective information related to the winter wheat chlorophyll content. The selected optimal spectral index combinations at various scales were used as the input variables, and three machine learning methods, GA-BP, SVM and RF, were employed to construct models for estimating the winter wheat chlorophyll content [44]. Among the three machine learning methods, the model based on the GA-BP method exhibited the highest accuracy for estimating the winter wheat chlorophyll content. Shi et al. [45] showed the highest accuracy of inversion of chlorophyll content in winter wheat using the GA-BP model, with an R^2 of 0.952, which was consistent with the results in this study. This indicates that the GA-BP method has a stronger capability to extract chlorophyll content information from spectral reflectance data. This is attributed to the integration of the genetic algorithm and back propagation neural network advantages in the GA-BP algorithm, which help in selecting the most representative input features, enhancing the model's generalization ability and prediction accuracy, and enabling the learning and capture of complex nonlinear relationships in the data. However, due to the combination of two algorithms, GA-BP often requires more time to complete training and may be constrained by the local optima, leading to suboptimal results. The prediction accuracy of the RF method is slightly lower than that of the GA-BP method, which may be due to the increased difference in the number of high and low content samples in the sample, which may form the model's preference for a certain category and affect the overall accuracy. The SVM method had the lowest prediction accuracy, which can be attributed to the high computational complexity of SVM algorithms when dealing with high-dimensional feature spaces or large-scale datasets. This leads to long training times and high memory consumption, and also increases the risk of overfitting the model.

Nowadays, modeling of the crop chlorophyll using hyperspectral data has achieved good results in practical applications of the model. R^2 can serve as a comprehensive evaluation of the model's predictive accuracy, providing a basis for accurate monitoring of the crop conditions. Meanwhile, RMSE and MRE reflect the stability of the model, offering

relatively concentrated prediction results and providing a scientific basis for precision agriculture development [46]. But, currently, there are still many technical limitations, such as insufficient depth mining of spectral data information. In addition, because the performance of machine learning models is affected by the number of samples, parameter tuning, data quality, and other factors, there may be problems such as overfitting or underfitting [47]. To address the above problems, future research can try to improve the monitoring and estimation of crop chlorophyll content by evaluating the deep learning model for hyperspectral data analysis and designing the network structure [48], loss function [49], and training algorithm that are suitable for the characteristics of the field [50], as well as continuously optimizing and improving the machine learning model. These methods can more effectively utilize the information of hyperspectral data to enhance the understanding of the relationship between crop growth physiological state and chlorophyll content, and provide a reference for the use of multisource remote sensing such as hyperspectral to predict the chlorophyll content of winter wheat at the pulling stage with further exploration of hyperspectral reflectance continuous wavelet transform.

5. Conclusions

After performing continuous wavelet transform on the hyperspectral reflectance data, the correlation between the selected spectral indices and winter wheat chlorophyll content showed a significant improvement. When the modeling method was the same, but the input combinations differed, the predictive model accuracies ranked as follows: 2^6 , 2^3 , 2^5 , 2^2 , 2^0 , 2^4 , and 2^7 . On the other hand, when the input combinations were the same but the modeling methods varied, the predictive model accuracies ranked as follows: GA-BP, RF, and SVM. By considering various evaluation metrics, it was identified that the scale variation of 2^6 and the GA-BP method were the optimal transformation scale and modeling approach in this study. The predictive models constructed based on these parameters exhibited R^2 values of 0.858 and 0.859, RMSE values of 1.281 and 1.366, and MRE values of 2.621% and 2.920% for the training and validation sets, respectively.

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