The rapid detection method of chlorophyll content in rapeseed based on hyperspectral technology

Hongyuan TANG[1,2], Guiping LIAO[1,*]

[1] Agricultural College, Hunan Agricultural University, Changsha, 410128, China

[2] Basic Teaching Department, Changsha Vocational and Technical College, Changsha, China

*Correspondence: liaoguiping_135@163.com

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Abstract: The inconsistency of chlorophyll content in rapeseed directly affects the quality of seed, so it is necessary to establish a rapid and non-destructive detection technology of chlorophyll in mature rapeseed. In this paper, the content of chlorophyll in rapeseed samples was determined by ultraviolet-visible spectrophotometry, and the near-infrared spectrum data were collected. The partial least squares regression model of chlorophyll content in rapeseed was established based on hyperspectral technology through first derivative and standard normal variable transformation pretreatment. The results of the cross-test showed that the determination coefficient of the validation set of the prediction model of chlorophyll content in rapeseed was greater than 0.85, and the

root means square error (RMSE) of the cross-test was less than 0.3 mg/kg. The results showed that the method could accurately predict the chlorophyll content in rapeseed and provide important technical support for rapid monitoring of seed quality.

Key words: Hyperspectral technology, rapeseed leaf, chlorophyll, rapid detection

1. Introduction

Rapeseed (*Brassica napus* L.) plays an important role in the world's oil crops and is one of the world's four major oil crops e.i. soybean, sunflower, rapeseed, peanut (Chaghakaboodi *et al*., 2021; Bakhshi *et al*., 2021a,b; Zirgoli and Kahrizi, 2015).). Its planting area accounts for more than the total area of oil-bearing crops in China, and its output accounts for more than the total output of oil-bearing crops in China. It is an oil-bearing crop with strong adaptability, wide use, high economic value and great development prospect. Rapeseed oil is the largest source of edible vegetable oil in China, accounting for more than 50% of domestic edible vegetable oil (Jahangiri and Kahrizi, 2015; Jahangiri and Kahrizi, 2015; Xia et al., 2019). Rapeseed oil is rich in unsaturated fatty acids, phytosterols, tocopherols, polyphenols and other nutritional components, and the composition of fatty acids is balanced, which is one of the healthiest edible vegetable oils (Kakaei and Kahrizi, 2011; Kahrizi, 2014; Sonobe et al., 2020).

Chlorophyll is a group of chromogenic groups existing in plants in various forms, and its derivatives are photosensitizers (Ghobadi et al., 2011; Shahadati-Moghaddam et al.,

2017). Under high-intensity light, the existence of chlorophyll will increase the photooxidation rate, cause a free radical reaction, promote lipid oxidation, lead to rancidity and deterioration of the oil, greatly reduce the stability of oil and shorten the shelf life of products. The chlorophyll content in fruits and vegetables is related to freshness. Spinach has high chlorophyll content, but poor stability. It is afraid of light, heat and oxygen, which often leads to discoloration of fresh vegetables during storage. It was found that chlorophyll will decompose during storage, and cold storage can prolong the decomposition rate of pigment. The decomposition rate of green pigment first increases and then slows down with the storage time, showing a stable and regular change (Viégas et al., 2018). Chlorophyll is one of the important quality parameters of rapeseed. For rapeseed with high chlorophyll content, decolorization and deodorization are complex in the process of oil processing, resulting in higher processing costs. Moreover, the level of chlorophyll content will also affect the appearance quality and nutritional quality of vegetable oil (Liu et al., 2019). According to the Canadian grain Commission data, the chlorophyll content in rapeseed oil and seed is similar (Zhu et al., 2020).

With the advancement of rapeseed production mechanization in China, there is a big difference in the mature period of horned pericarp at harvest time, and the chlorophyll content in rapeseed increases significantly. In order to meet the quality control of raw materials in the purchase, storage and processing, it is necessary to establish a rapid and non-destructive detection technology for chlorophyll in rape. Non-destructive testing technology of agricultural products is a new technology that uses its physical properties such as mechanics, optics, electricity and acoustics to carry out non-destructive testing on its quality, and carries out classification and sorting according to certain standards

(Guo et al., 2019). At present, machine vision technology and spectrum technology are widely used in non-destructive testing of agricultural products because of their non-destructive, fast and reliable characteristics. Machine vision technology can effectively detect the external quality of agricultural products. The detection of the internal quality of agricultural products, such as protein, moisture, sugar content, acidity, etc., mainly relies on spectral technology, especially near-infrared spectroscopy (Ling et al., 2019). However, near-infrared spectroscopy can only detect a very small area of the detection object, and cannot carry out large-scale spatial detection. It has great limitations, which may lead to a large information difference between the modeling set and the prediction set, and thus cannot obtain a stable detection system (Namdaran Gooran et al., 2021).

Hyperspectral imaging technology can obtain the spectral and spatial information of the research object at the same time. Spectral data can analyze the internal physical structure and chemical composition of objects, and image data can reflect the external characteristics, stains and surface defects of agricultural products. Therefore, in recent years, hyperspectral imaging technology has attracted more and more attention in the nondestructive testing of agricultural product quality (Wang et al., 2019). In foreign countries, hyperspectral imaging non-destructive testing technology started earlier, focusing on the quality of fruits and meat, there are also some studies in other agricultural products. In China, there are more researches on nondestructive testing of fruit quality, such as surface damage, internal components, etc., as well as non-destructive testing of meat, vegetables, crop seeds, etc. A large number of studies have proved that the contents of chlorophyll, carotenoids and anthocyanins in plants have their unique spectral absorption characteristics, and the characteristic bands are 640-660 nm, 430-450 nm and 537 nm (Kovar et al., 2019). The quantitative inversion of plant

pigment was realized by hyperspectral technology, and then the physiological characteristics of plant senescence, diseases and insect pests and environmental stress (water and temperature) were retrieved. The results were highly significantly correlated with the experimental results obtained by traditional methods (Corti et al., 2017).

At present, the application of hyperspectral imaging technology in the non-destructive testing of agricultural products is still in the initial stage of development. With the continuous improvement of experimental instruments and spectral resolution, hyperspectral imaging can record more and more abundant quality information of agricultural products, which will be an important tool for rapid and non-destructive detection of agricultural products quality. Because of its high content but poor stability, fresh vegetables often appear yellowing and fading during storage. Therefore, chlorophyll is often used to evaluate the freshness quality of rape.

The main detection method of chlorophyll is ultraviolet-visible spectrophotometry, which has high sensitivity and reliable results, but the detection cost is high due to the high cost of consumables and equipment needed, and it can not meet the needs of on-site detection of acquisition, processing and other links. In this paper, the contents of chlorophyll a, chlorophyll b and total chlorophyll in rapeseed samples were determined by chemical experiments. Combined with visible and near-infrared hyperspectral imaging technology, a variety of chemometrics methods were used to establish the prediction model of chlorophyll a, chlorophyll b and total chlorophyll in spinach leaves, aiming to explore a stable rapid and non-destructive detection of chlorophyll content in rapeseed for the future The application of hyperspectral technology in the rapid classification of rapeseed chlorophyll provides strong technical support.

2. Materials and methods

2.1. Hyperspectral image acquisition

According to the cube, the number of hyperspectral images can be regarded as the superposition of gray images in each band. It can not only provide the spectral band information of each pixel in the image but also provide the gray image under a certain band (Kaya et al., 2019). These gray images contain rich spatial distribution characteristics of samples, and spatial distribution information can be extracted by image processing technology. Spectral features and texture features are two basic features of hyperspectral images, and they are also the two basic elements for hyperspectral image analysis. Texture analysis is the process of extracting and analyzing the spatial distribution patterns of images, so as to obtain the qualitative or quantitative description of texture features.

2.1.1. Pretreatment of hyperspectral analysis

The pretreatment of hyperspectral technology analysis is mainly aimed at specific sample system, eliminating abnormal samples, eliminating spectral noise, screening data variables, optimizing spectral range, so as to reduce the impact of non-objective factors on the spectrum, and lay the foundation for establishing spectral correction model and predicting unknown sample information (Sun et al., 2018). The pretreatment process is divided into two aspects: sample pretreatment, including the elimination of abnormal samples and the screening of modeling, set samples. The elimination of abnormal samples is based on the prediction of concentration residual, principal component score clustering, Mahalanobis distance calculation, leverage value and Student t-test. The selection of modeling set samples is mostly based on conventional

modeling sample selection methods, such as the content gradient method, Kennard stone method and so on. Through screening, the number of samples of basic measurement data can be effectively reduced, and the cost of modeling can be reduced. spectral preprocessing includes spectral noise elimination and spectral feature extraction. In addition to the information of specific components of the sample, the collected spectra also contain other irrelevant information and noise, such as electrical noise, sample background and stray light. It is necessary to establish a quantitative model to eliminate noise. The commonly used methods are spectral smoothing, derivative, light scattering correction, wavelet transform, orthogonal signal correction and so on. In addition, by optimizing the spectral range and extracting the characteristic bands, the irrelevant variables can be eliminated effectively, and the calculation efficiency and prediction ability can be improved, thus a more robust correction model can be established. The commonly used wavelength selection methods include the correlation coefficient method, stepwise regression method, interval partial least squares method, genetic algorithm and so on.

2.1.2. Obtaining hyperspectral information of rapeseed leaves

The leaf image information was collected by a hyperspectral imaging system within three hours after rapeseed samples were collected. Firstly, focus the inspector v10e high spectral imager, set the exposure time of the system to 0.06 s, and the moving speed of the mobile platform to 3.5 mm/s. In order to eliminate the influence of different lighting conditions and environmental factors on the image acquisition quality, a white board and dark environment were used to calibrate the hyperspectral imager. Before each experiment, white board made of polytetrafluoroethylene was

used for white board correction, and then the light source and lens cover were closed for dark environment correction. After correction, the blade of rapeseed was placed flat on the measuring platform, and the hyperspectral image data was collected. The image resolution of the hyperspectral camera is 672 × 512, and the spectrum range is 380-1030 nm, with a total of 512 bands. The original image is corrected according to formula (1).

$$I = \frac{I_0 - B}{W - B} \tag{1}$$

In formula (1), I is the calibration image of the sample, I0 is the original image of the sample, and B is the calibration image in an all black environment (reflectance close to 0%, white standard image (reflectance close to 99%). The effect of different spectral conditions on the image of the measured object is different. Hyperspectral image data acquisition is based on spectral cube (v10e and n17eisuzu optics Corp., China) software platform.

2.1.3. Establishment and evaluation of hyperspectral estimation model

The flow chart of establishing spectral prediction model is shown in Figure 1. Firstly, a certain number of samples are selected, and their chemical values of component content are measured by standard chemical method, and their spectral signals are measured by spectrometer; these samples are divided into modeling set and prediction set, and statistical regression method (such as multiple linear regression) is used through the relationship between spectral signal and chemical value of modeling set (MLR), principal component regression (PCR), partial least squares (PLS) and artificial neural network (ANN) were used to establish the calibration model; further, the calibration model was tested by predicting the corresponding chemical value of

component content through the spectral signal of the prediction set and the established calibration model (Lu et al., 2020).

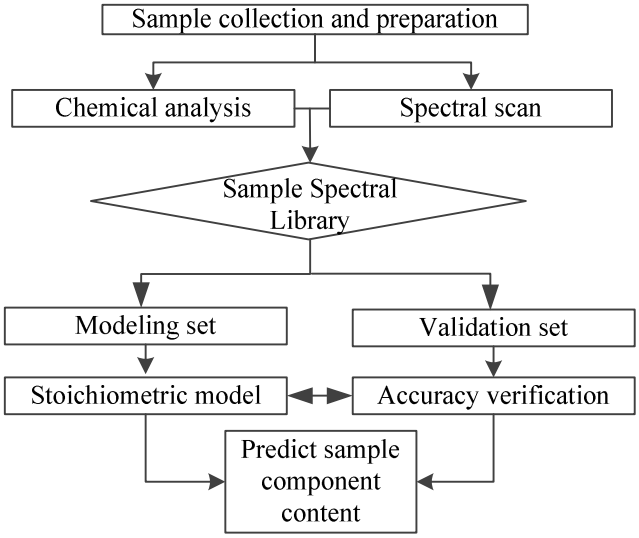


Figure 1. Analysis flow of hyperspectral technology.

When the quantitative model based on the hyperspectral image is established, the performance of the model needs to be evaluated quantitatively to judge the advantages and disadvantages of the model. The prediction performance evaluation indexes of the model established by the chemometrics modeling method mainly include the correlation coefficient and root mean square error between the sample measured value and the predicted value. The closer the correlation coefficient (RC) is to the root mean square error, the better the prediction performance and the higher the prediction accuracy. In this study, the correlation coefficient of prediction set samples and the root mean square error of prediction set samples are the main discriminant criteria, and the correlation coefficient (RMSEC) and root mean square error (RMSE) of modeling set samples are used as auxiliary criteria. The calculation formula of correlation coefficient and root mean square error (Wu et al., 2018) is as follows:

Correlation coefficient (R)

$$R = \frac{\sum_{i=1}^{n}(x_i - \overline{x})(y_i - \overline{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \overline{x})^2}\sqrt{\sum_{i=1}^{n}(y_i - \overline{y})^2}} \quad (2)$$

In formula (2), xi is the measured value of sample I; $\overline{x}$ is the average value of xi; yi is the predicted value of sample I; $\overline{y}$ is the average value of yi; n is the number of samples.

Root mean square error (RMSE):

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - y_i)^2} \quad (3)$$

In formula (3), xi is the measured value of sample I; yi is the predicted value of sample I.

The larger the R^2 value of interactive verification of modeling set is, the more stable and accurate the model is; the smaller the R^2 value and RMSE of validation set are, the better the prediction effect is.

2.1.4. Chemometrics modeling method

Hyperspectral image data contains rich spectral information and image texture information, which is used to reflect the composition, properties and structure of substances. However, due to a large amount of information and the fact that important information is often covered up, it is usually impossible to establish a qualitative and quantitative relationship model between the spectral and texture information and the characteristics of material targets. Therefore, it is necessary to use a chemometrics algorithm for data mining and feature extraction of original Hyperspectral Information.

As long as the new sample is input into the model quickly, the new sample can be processed quickly. A partial least square method is used in this modeling.

Partial least squares (PLS) is the most commonly used multivariate statistical method in chemometrics modeling and analysis and is widely used in spectral data modeling and analysis (Zhang et al., 2020). The principle is to decompose the spectral matrix and the target feature matrix into multiple latent variables (LVS) simultaneously by factor analysis. The order of potential variables is following their contribution rate. Based on the cumulative contribution rate of the first several potential variables and the performance of the model established based on the number of different potential variables, the optimal number of potential variables was selected for regression calculation. Meanwhile, spectral data variables and chemical index data variables were considered, so the performance of the model was better. The calculation process is as follows:

$$X = TP + E \tag{4}$$

$$Y = UQ + F \tag{5}$$

T and U are the score matrix of matrix X and matrix Y respectively, P and Q are the load of matrix X and matrix Y respectively, i.e. principal component) matrix and E and F are the errors introduced when fitting X and Y with the PLS model respectively.

Let T and U be linear regression. B is the correlation coefficient matrix:

$$U = TB \tag{6}$$

$$B = TU(TT)^{-1} \tag{7}$$

In the prediction, the TP of the unknown sample x matrix is obtained from the matrix XP of the unknown sample and the corrected PV. The results are as follows:

$$Y_P = T_P BQ \tag{8}$$

When building a PLS model, how to select the optimal number of potential variables is very important. When the number of potential variables is small, the selected potential variables cannot replace the spectral characteristics of the samples, resulting in the decline of the prediction accuracy of the model; when the number is too large, the noise interferes with the model will be introduced. Calculating the sum of squares of predicted residuals (press) is a common criterion for selecting the optimal number of potential variables. The larger the press is, the greater the model error is, while the higher the press is, the higher the prediction accuracy of the model is. At present, there are many methods to calculate the sum of squares of residual errors, including the leverage point prediction method, self prediction method and interactive verification method, and the most commonly used method is the interactive verification method. The interactive verification method selects some samples from the modeling samples as the verification samples and the remaining samples as the modeling samples. A series of validation models are obtained through the cycle. Then calculate the model to select the optimal number of potential variables. Due to the repeated cycle modeling, the interactive verification method can well verify the accuracy of the model and whether it is overfitted, to avoid the model performance difference caused by a different selection of modeling samples.

2.2. Rapid detection of chlorophyll content in rape

2.2.1. Preparation of rapeseed samples

The chemical value measurement method of rapeseed leaf nutrients will be taken back to the laboratory from the field. First, the soil and other debris on the leaves were wiped and cleaned, and then the hyperspectral image was obtained. Then, the leaf samples were put into a sealed bag and put into the oven at 110 °C for 30 min. After

sterilization, the leaves were dried in an oven at 60 °C for 10 h and weighed with a balance until the weight of the leaves did not change.

2.2.2. Determination of chlorophyll content

The rapeseed leaves were quickly cut and weighed accurately about 0.1 g and weighed once on the left and right sides of the leaves respectively. The chlorophyll-a value of each sample was measured twice, and the average value was finally taken, and the vein part of the leaf was avoided as far as possible. Then cut into thin filaments and transfer into a clean centrifuge tube. Add 10 ml of 95% ethanol extract into the tube. Keep the sample completely white at room temperature (shake the extract several times during this period). The extraction solution is measured by UV-Vis spectrophotometer at the wavelength of 665, The whole experiment was carried out at 4 °C. The content of chlorophyll a was calculated according to formula (9) and formula (10), and the unit was mg/g.

$$Chla(mg/L) = 13.95D665 - 6.88D649 \quad (9)$$

$$Chla(mg/g) = [C(mg/L) \times V(ml)]/[m(g) \times 1000] \quad (10)$$

The residual method was used to eliminate the abnormal samples. In this study, nine abnormal samples were eliminated, and the remaining 81 samples were randomly divided into 54 modeling set samples and 27 prediction set samples according to the ratio of 2:1. The number, range, mean value and deviation of total chlorosin content in total samples, modeling sets and prediction sets are shown in Table 1.

Table 1. Statistical results of chlorophyll-a content in each sample set

Sample category	Number of samples	Range	Mean value	Standard deviation
Total sample	81	0.7589-3.3993	2.0439	0.4145
Modeling set	54	0.7589-3.3993	2.0591	0.4408
Survey set	27	1.1613-2.6727	2.0136	0.362

The calculation formula of chlorophyll b content is as follows:

$$Chlb(mg/L) = 24.96D649 - 7.32D665 \quad (11)$$

$$Chlb(mg/g) = [C(mg/L) \times V(ml)]/[m(g) \times 1000] \quad (12)$$

The residual method was used to eliminate the abnormal samples, and 10 abnormal samples were eliminated. The remaining samples were randomly divided into 62 modeling set samples and 28 prediction set samples according to the ratio of 2:1, which were used for modeling and prediction respectively. The number, range, mean value and deviation of chlorophyll content of the total sample, model set and prediction set are shown in Table 2.

Table 2. Statistical results of chlorophyll b content in each sample set.

Sample category	Number of samples	Range (mg/g)	Mean value (mg/g)	Standard deviation
Total sample	90	0.2985-0.8624	0.5928	0.1158
Modeling set	62	0.2928-0.8659	0.6251	0.1186
Survey set	28	0.3258-0.8294	0.5864	0.1182

The total chlorophyll content is the sum of chlorophyll a and chlorophyll b, which is calculated according to the following formula.

$$Chl(a+b)(mg/L) = Chla + Chlb = 18.08D645 + 6.63D663 \quad (13)$$

$$Chl(a+b)(mg/g) = [C(mg/L) \times V(ml)]/[m(g) \times 1000] \quad (14)$$

The residual method was used to divide the abnormal samples, and 15 abnormal samples were eliminated. The remaining samples were randomly divided into 70 modeling set samples and 30 prediction set samples according to the ratio of 2:1, which were used for modeling and prediction respectively. The number, range, mean value

and deviation of total chlorophyll content of total samples, modeling sets and prediction sets are shown in Table 3.

Table 3. Statistical results of total chlorophyll content of each sample set.

Sample category	Number of samples	Range(mg/g)	Mean value (mg/g)	Standard deviation
Total sample	100	0.9748-3.7982	2.2864	0.5075
Modeling set	70	0.9748-3.7659	2.3481	0.5018
Survey set	30	1.1685-3.4825	2.2949	0.5049

2.2.3. Prediction model of chlorophyll-a content based on the full band

The whole leaf of rapeseed was selected as the region of interest (ROI) by envi4 software, and then the average spectral curve in the region of interest was extracted. Cut off the noise of 380-438 nm and 945-1023 nm of the whole spectrum, and retain the average spectrum in the range of 439-943 nm (400 bands), and obtain the visible and near-infrared spectra of 81 rapeseed samples at 20 ℃ as shown in Figure 2.

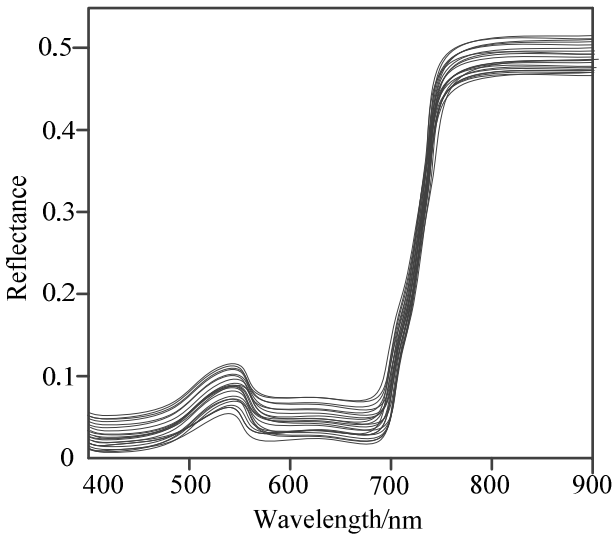
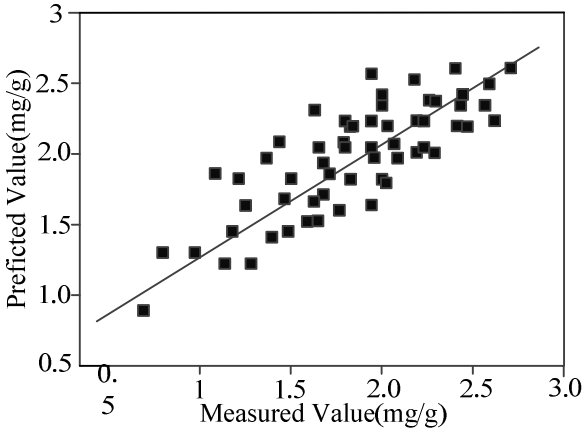


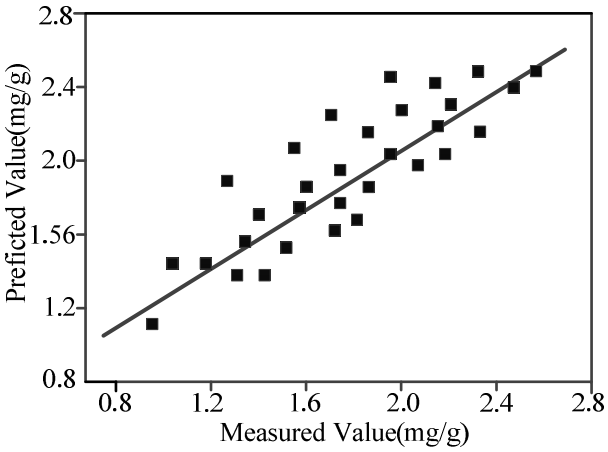
Figure 2. The spectral curve of rapeseed sample for chlorophyll detection.

54 samples of modeling set were used for PLS modeling, and the full band prediction model of total chlorosis in rapeseed leaves was obtained. The model was tested with 27

prediction set samples. The scatter diagram of the PLS model for prediction of modeling set and prediction set sample is shown in Figure 3 (a, b). The correlation coefficient $r_c = 0.8991$, RMSE = 0.1912 and $r_p = 0.8393$, RMSE = 0.1933. The full spectrum PLS model can effectively predict the total chlorophyll content.



(a) Modeling set



(b) Prediction set

Figure 3. Scatter plot of full-spectrum PLS model for prediction of chlorophyll a.

2.2.4. Prediction model of chlorophyll b content based on the full band

The visible and near-infrared spectra of rapeseed samples with chlorophyll content b are shown in Figure 4.

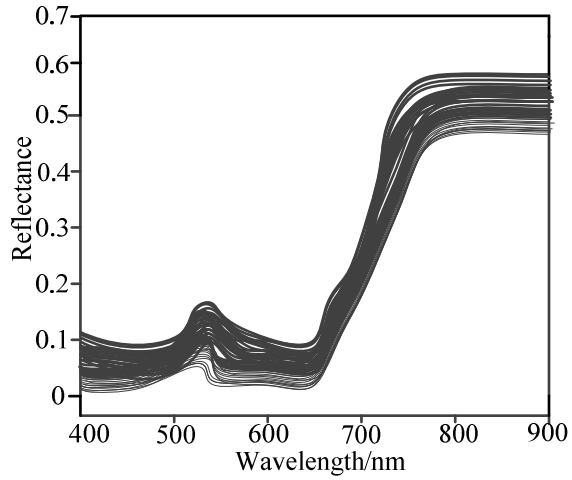
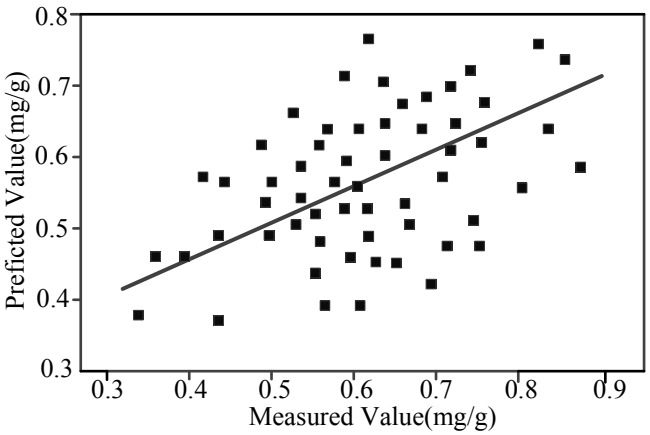
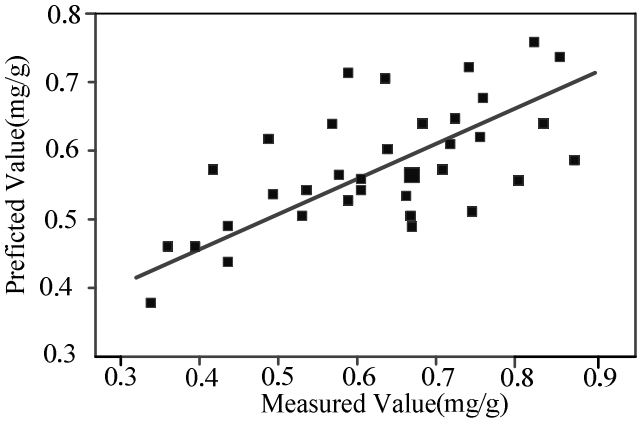


Figure 4. The spectral curve of rapeseed sample for chlorophyll b detection.

The full band prediction model of spinach leaf chlorophyll b was obtained by PLS modeling with 90 modeling set samples, and then the model was tested with 64 prediction set samples. The scatter diagram of the PLS model for prediction of modeling set and prediction set sample is shown in Figure 5 (a, b). The correlation coefficient of prediction set is RC = 0.8952, rsepc = 0.0869, correlation coefficient of prediction set prediction is RC = 0.8856, rsepc = 0.0876. The results show that the full spectrum model can obtain satisfactory prediction results and obtain an ideal prediction effect.



(a) Modeling set



(b) Prediction set

Figure 5. Scatter plot of full-spectrum PLS model for prediction of chlorophyll a.

2.2.5. Prediction model of total chlorophyll content based on the full band

The visible and near-infrared spectra of rapeseed samples for detecting total chlorophyll content are shown in Figure 6.

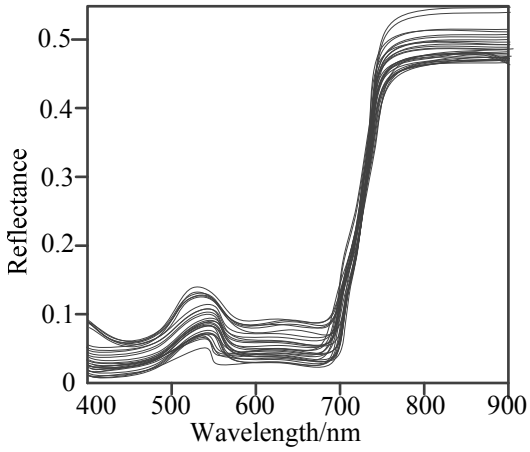
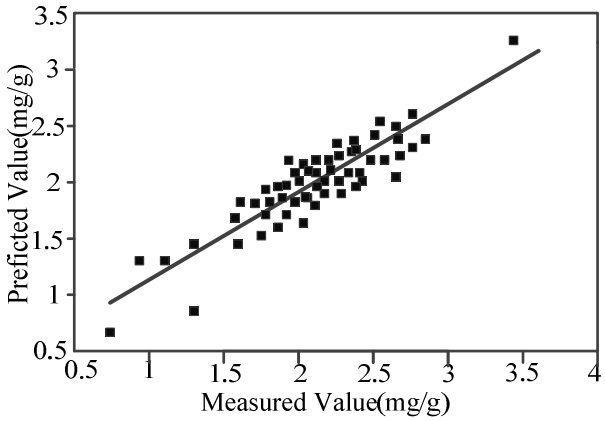


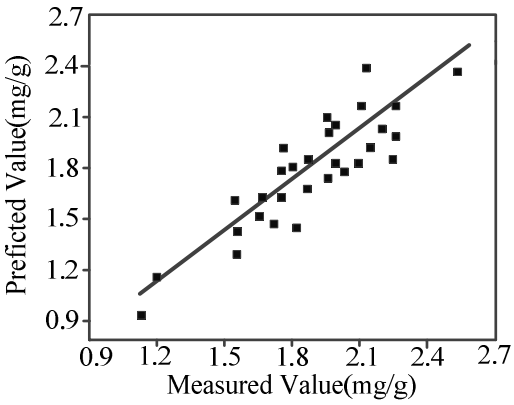
Figure 6. The spectral curve of rapeseed sample for total chlorophyll detection.

The full band prediction model of total green content in leaves of Chinese cabbage was obtained by PLS modeling with 100 modeling set samples. The model was tested with

70 prediction set samples. The scatter diagram of PLS model for prediction of modeling set and prediction set sample is shown in Figure 7. The correlation coefficient of the model set prediction is RC = 0.8452, rsepc = 0.2785, the correlation coefficient of prediction set prediction RP = 0.8449, rsepc = 0.2964. The results show that the full spectrum model can effectively predict the total chlorophyll content, in order to obtain a better prediction effect.



(a) Modeling set



(b) Prediction set

Figure 7. Scatter plot of full-spectrum PLS model for prediction of total chlorophyll.

3. Discussion

Hyperspectral technology has great potential in the field of ecology due to its high spectral resolution. However, there are still some problems to be solved and improved

in practical application: The accuracy of hyperspectral inversion and its application range is limited

Compared with the traditional chemical analysis methods, hyperspectral technology can obtain better prediction accuracy in the inversion of ground feature attributes, which has the advantages of fast, non-destructive, low-cost and repeatable. However, in the research which requires high precision, the prediction results often can not support the original scientific hypothesis, or even cause the opposite research results. For example, hyperspectral technology in soil detection, soil organic matter and water content prediction results are good, but the prediction ability of trace elements (such as boron, zinc, copper) is limited. In addition, due to the limitation of visible and near-infrared spectral penetration, hyperspectral technology can only retrieve the apparent parameters of ground objects (such as topsoil, upper forest canopy, etc.), but cannot predict the internal component parameters of ground features, which limits the application scope of hyperspectral technology. Therefore, in future research, we should deeply tap the potential of spectral technology. While exploring new modeling methods to improve the prediction accuracy, we need to comprehensively consider the mechanism of surface features and spectrum, and better use hyperspectral technology to accurately obtain the apparent parameter information of ground objects.

Hyperspectral modeling is easily disturbed by external factors: Because the research object of ecology is often the combination or mixture of different substances, its spectral information is also interfered with by other irrelevant information and noise, such as background, stray light and instrument noise, so it is necessary to eliminate the interference of these external factors. At present, the commonly used methods include data smoothing, derivative transformation, light scattering correction and so on. In

recent years, new methods such as orthogonal signal correction, wavelet transform and orthogonal external factors have been developed and applied to eliminate the interference of external factors, and the prediction ability of the model has been improved in varying degrees. Therefore, how to better use the new stoichiometry method to eliminate the interference of external factors in the mixed spectrum is a very important content in future hyperspectral technology research.

Hyperspectral inversion model lacks universality: At present, there are a lot of ground feature attribute inversion models established by hyperspectral technology, but there is still no universal model method for the same kind of ground features. The spectral information required by each model is significantly affected by temperature, light conditions, instrument installation, etc.; and for the same ground objects (such as hyperspectral technology has become one of the frontier technologies in the field of ecological data acquisition), the technology relies on the response mechanism of surface feature spectrum, and can accurately monitor the evolution process information of ecosystem, which provides the basis for the rapid development of ecology. At present, hyperspectral technology has made a lot of research results in the field of soil, plant physiology, agricultural product quality detection and ecosystem carbon cycle, but it is still in the initial stage and development stage. Mature hyperspectral technology needs to be explored and studied continuously. With the development of remote sensing technology, the application of hyperspectral remote sensing extends the spectral analysis technology to the spatial domain, which provides a broader application prospect for the large-scale data mining and ecological modeling of ground objects spectral information, and is expected to become a new mode of data acquisition for future ecological development.

4. Conclusion

Based on hyperspectral imaging technology, taking rapeseed leaves as the research object, spectral preprocessing was carried out. The chemical index characteristic wavelengths of rapeseed leaves were determined by various characteristic wavelength selection methods. The contents of chlorophyll a, chlorophyll b and total chlorophyll were calculated. The detection method of chlorophyll content was established by the chemical index prediction modeling method Good modeling results are obtained. The results of this study provide a reference direction and theoretical basis for further exploring the stable and reliable detection of chlorophyll content in vegetables. However, due to the limited time and energy, further research is needed in the following aspects: However, there are many kinds of rape, and there are great differences between different varieties. It is not clear whether this conclusion applies to other varieties of rape. Therefore, the follow-up experiments should be based on the study of different varieties of the same vegetable, or extended to the study of multiple vegetables. The experimental study combines the chemical detection method and spectral non-destructive testing, the sample size for modeling analysis can not be too small, but the increase of sample size will increase the difficulty of chemical index detection and will reduce the accuracy of the results. In order to achieve the research results, it is suggested that the number of indexes detected in each experiment should not be too much, and the experiments should be carried out separately many times. In addition, several chemical indexes studied in this paper are not comprehensive enough, and the content of pigment varies greatly in different vegetables, so it is difficult to be widely used.

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