Study on Chlorophyll Content in Visible-Near Infrared Spectroscopy

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Abstract. Chlorophyll, as an important factor for the normal growth and development of plants, is of great significance for the management of agricultural water and fertilizer. In this study, the chlorophyll content of maize leaves was taken as the research object, and the chlorophyll content prediction model was quantitatively studied. ASD FieldSpec Pro spectrometer was used to measure the spectral reflectance of the leaf samples, and the spectral curve characteristics of different contents were analyzed. The results show that: (1) The reflection spectrum undergoes the nine-point smoothing of Savitzky-Golay and combines with the MSC, NOR, and SNV transforms to significantly increase the signal-to-noise ratio of the reflection spectrum. The combination band with higher correlation can significantly improve the stability and prediction of the model ability. (2) In the PLSR model, MSC processing is performed on the smoothed spectrum, and the model established after the second-order differential transformation has the best effect, $R^2 = 0.95$, RMSEC = 2.32, SEC = 1.35.

Keywords: Sensitive band; chlorophyll, spectral reflectance, hyperspectral prediction model.

1. Introduction
In recent years, domestic and foreign scholars have conducted a lot of researches on estimating the chlorophyll content of leaves using hyperspectral inversion in the visible range, but there are few studies on the estimation in the whole band [1, 2]. Using a unified spectral index to establish a wheat chlorophyll content estimation model, and obtained good prediction results [3]. Analyzed the correlation between hyperspectral reflectance and chlorophyll density, and found that the red edge position is the sensitive band of chlorophyll [4]. The chlorophyll concentration of the four crops was predicted using the single-leaf directional reflectance normalized by the green band and the red edge.
to calculate a new vegetation index [5]. The study found that the chlorophyll concentration of vegetation can be estimated using the wavelength of the derivative spectrum at the maximum near 700 nm [6]. Using wavelet analysis, a hyperspectral inversion model of soybean chlorophyll a was established. The reflection spectra of single leaf and canopy of cotton at key growth stages were studied, and the correlation between hyperspectral data and cotton chlorophyll content and chlorophyll density was analysed [7]. Using the spectral vegetation index, a monitoring model between apple leaf hyperspectral parameters and pigment content was established, and spectral parameters highly sensitive to pigment content were selected [8].

With the development of chemometrics, the spectral feature extraction has become more accurate, and the spectral information with complex components and overlapping peaks can be effectively extracted, and the near-infrared analysis technology has been effectively used in the estimation of chlorophyll content. At present, hyperspectral remote sensing has made great progress in monitoring the chlorophyll content of corn, wheat and other crops.

2. Materials and methods

2.1. Soil sample collection
Use random block design, set points and random sampling according to its distribution characteristics to ensure the representativeness of its samples. Randomly select 10 canopy leaves of different heights and different levels in each direction of the test plot to measure the spectral reflectance, and simultaneously collect the non-destructive and regular-shaped leaves and quickly put them into the fresh-keeping bag and bring them back to the laboratory, totaling 120 Pc

2.2. Spectral data determination
In each experimental area, 10 canopy leaves of different heights and different levels were randomly selected to measure the spectral reflectance. After each measured spectral data, a standard whiteboard optimization was performed. During the measurement, 10 spectra were collected from each leaf, and the average value was obtained after removing the abnormal spectrum as the canopy spectral reflection value of the sample.

2.3. Data Pretreatment
Samples will introduce different levels of outliers in the process of collection, processing and analysis, especially that the measurement error will affect the accuracy of later data analysis and modeling. Based on the multivariate normal distribution and considering the three factors of covariance, mean and variance, this study uses the Euclidean distance method to detect outliers for attributes and data.

2.4. Modeling and inspection
Randomly divide the original data into two groups, 70% establish a chlorophyll content prediction model, and 30% samples are used as the verification of the inversion model. The correlation analysis is processed using SPSS17.0, and PLSR modeling is implemented in TQ Analyst. The determination coefficient R2 and the root mean square error RMSE of the predicted value and the measured value are used to verify the inversion model.

3. Results and analysis

3.1. Corn chlorophyll content
The collected fresh leaves are first wiped off with pure cotton spectacles to clean the surface dirt, and then shredded and mixed. Weigh about 0.2 g of the shredded fresh sample into a mortar. 10 mL of ethanol solution with a concentration of 10%. After shading at room temperature and leaving the sample completely white, the extract was colorimetrically measured with a spectrophotometer. Corn chlorophyll content statistics are as follows:
Table 1 The statistics of chlorophyll

| Plant | (Max mg g⁻¹) | (Min mg g⁻¹) | (Mean mg g⁻¹) | SD  |
|-------|--------------|--------------|---------------|-----|
| Crop  | 115.4        | 24.4         | 75.3          | 21.43 |

3.2. Correlation analysis
Spectral differential processing can not only eliminate the effects of baseline drift and smooth background interference, but also obtain characteristic bands, and effectively reduce the impact of low-frequency background on the target spectrum. Correlation analysis results of different differential processing of the reflection spectrum and chlorophyll content show that the chlorophyll content and the original spectral reflectance are negatively correlated in the bands of 511 ~ 548 nm, 710 ~ 1589 nm, 1697 ~ 2379 nm and in The band from 2044 to 2139nm reaches a significant negative correlation and can be used as a sensitive band for chlorophyll. After the differential transformation of the reflection spectrum, the significance increases significantly (Fig.1).

![Fig 1 The Correlation Coefficient](image1)

3.3. Prediction Model
PLSR is used to establish different estimation models for different spectral indexes. Both the modeling accuracy and prediction accuracy of the regression model established after preprocessing and differential transformation are better than those based on the original data. After processing the smoothed spectrum, the model established after the second-order differential transformation has the best effect, $R_c^2 = 0.95$, RMSEC = 2.32, SEC = 1. 35.. After comparison, it can be found that the prediction model established by Savitzky-Golay nine-point smoothing of the original reflection and MSC preprocessing combined with second-order differential is the best (Fig.2).

![Fig 2 The Regression Coefficient of Model Based Partial Least Squares](image2)
4. Conclusions
This study is mainly to monitor the chlorophyll content of the canopy at the jointing stage. The correlation between the chlorophyll content and the hyperspectral characteristics is used to preprocess the reflection spectrum. The differential chromatic characteristic bands are extracted using different differential transformations. Quantitative model of content. This model provides a quicker method and way to estimate the chlorophyll content of rape in the study area.

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