Postprint of Cotton Leaf Chlorophyll Content Estimation Based on Combination of Multiple Vegetation Indices

Authors: Arzugul Rozi, Memet Sawut, He Xugang, Ye Xiaowen

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Abstract

Chlorophyll content is an important reference indicator for characterizing vegetation growth status. This study utilized hyperspectral technology to rapidly and accurately monitor chlorophyll content in cotton leaves, taking 125 cotton leaf samples at the seedling stage in Xinjiang as the research object. By measuring their chlorophyll content and spectral data, and employing a combination of multiple spectral preprocessing methods and multiple vegetation indices, a WOA-RFR quantitative inversion model for cotton leaf chlorophyll content was constructed, and its results were compared and analyzed with those of SVR and RFR models. The results indicate that: (1) Among spectral transformation methods, logarithmic transformation, fractional-order differential, and continuous wavelet transform can all effectively improve the correlation between vegetation indices and chlorophyll content. (2) The WOA-RFR model based on the combination of Vogelmann3, RVI, DVI, SR[675-700], Mndvi705, ND, VOG1, NVI, TVI, and VOG2 vegetation indices under 0.9-order fractional-order differential transformation achieved the best inversion performance, with model R^2 values of 0.920 and 0.955, RMSE values of 0.987 and 0.986, and MRE values of 0.013 and 0.014 for the modeling and validation sets, respectively. Compared with RFR and SVR models, the prediction accuracy was improved, and the optimization effect of the WOA algorithm on the model was significant. The research results can provide a decision-making basis for the quantitative inversion of cotton leaf chlorophyll content.

Full Text

Estimation of Cotton Leaf Chlorophyll Content Based on Multi-Vegetation Index Combinations

Areziguli ROZI[123], Mamat SAWUT[123], HE Xugang[123], YE Xiaowen[123]

[1]College of Geography and Remote Sensing Sciences, Xinjiang University, Urumqi 830017, Xinjiang, China
[2]Xinjiang Key Laboratory of Oasis Ecology, Urumqi 830017, Xinjiang, China
[3]Key Laboratory of Smart City and Environment Modelling of Higher Education Institute, Urumqi 830017, Xinjiang, China

Abstract

Chlorophyll content is a crucial reference indicator for characterizing vegetation growth status. This study utilized hyperspectral technology to rapidly and accurately monitor cotton leaf chlorophyll content. Using [number missing] cotton leaf samples at the seedling stage from Xinjiang as research objects, we measured their chlorophyll content and spectral data. By employing multiple spectral preprocessing methods combined with multi-vegetation indices, we constructed a quantitative inversion model for cotton leaf chlorophyll content and compared the results with [model name missing] model. (1) Spectral transformation methods including logarithmic transformation, fractional-order differentiation, and continuous wavelet transformation effectively improved the correlation between vegetation indices and chlorophyll content. (2) The Vogelmann3 Mndvi705 vegetation index combination model achieved the best inversion performance, with R^2 values of [values missing] for both the modeling set and validation set. Compared with the [model name missing] model, prediction accuracy was improved, and the algorithm optimization effect was significant. The research results can provide decision-making support for quantitative inversion of cotton leaf chlorophyll content.

Keywords: combination of vegetation index; cotton; chlorophyll content; whale optimization algorithm

Introduction

Chlorophyll content is a crucial indicator for characterizing crop health status and is closely related to crop growth [citation missing]. Traditional methods for determining chlorophyll content are costly, operationally complex, and inefficient, making them difficult to meet the demands of precision agriculture development [citation missing]. Currently, precise, rapid, and efficient hyperspectral technology has proven effective for vegetation chlorophyll content acquisition [citation missing]. Research on spectral inversion of cotton leaf chlorophyll content primarily employs combined preprocessing methods to analyze the correlation between spectra and chlorophyll content, selecting characteristic wavelengths or constructing hyperspectral vegetation indices to establish chlorophyll monitoring models [citations 1,3-4].

Scholars have utilized various spectral preprocessing methods such as wavelet transform [citation missing], first derivative [citation missing], second derivative [citation missing], and fractional differential transform [citation missing] to effectively reduce or even eliminate redundant hyperspectral information. Selecting appropriate spectral transformation methods can improve crop chlorophyll inversion accuracy. Similarly, the vegetation index method, as an important approach for hyperspectral inversion of crop physiological and biochemical indicators, has been widely applied in retrieving crop biochemical parameters [citation missing]. For instance, [author missing] used continuous wavelet transform to analyze potato chlorophyll content, demonstrating that this method can effectively extract sensitive and robust wavelet features for potato chlorophyll content, enhancing the correlation between spectra and chlorophyll content. [Author missing] conducted hyperspectral inversion of peanut leaf chlorophyll content and found [index name missing] to be the optimal spectral index.

With the rapid development of machine learning algorithms, multiple linear regression (MLR), partial least squares regression (PLSR), random forests regression (RFR), and support vector machine regression (SVMR) have all achieved good results in estimating leaf chlorophyll content. For example, Rukeya et al. [citation missing] used logarithmic transformation and fractional-order differential vegetation indices, finding that the [model name missing] model provided the best estimation accuracy. Guo Chaofan et al. [citation missing] proposed a multi-vegetation index collaborative estimation model with significantly improved accuracy compared to single vegetation index models. Therefore, selecting appropriate spectral preprocessing methods, vegetation index methods, and machine learning methods is particularly important for retrieving crop leaf chlorophyll content using spectroscopy.

Most previous studies are based on single spectral data transformation or single vegetation index modeling, while research on cotton leaf chlorophyll estimation using multiple spectral transformations and multi-vegetation index combinations is rarely reported. Therefore, this study combines previous research to select [number missing] vegetation indices widely used in crop parameter research. Based on traditional mathematical transformations, fractional-order transformations, and wavelet transformations, combined with correlation coefficient methods and the Whale Optimization Algorithm (WOA), we established multiple vegetation index regression models to address: (1) whether spectral data transformation methods can improve the correlation between vegetation indices and cotton leaf chlorophyll content; (2) the optimal vegetation index combination and best estimation model; and (3) the optimization effect of WOA compared to [model name missing] models.

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1. Materials and Methods

1.1 Study Area Overview The study area is located in Aksu Prefecture, Kuqa City, Xinjiang, specifically in Akosutang Township (82°58 –83°30 E, 41°16 –41°31 N), situated at the southern foothills of the Tianshan Mountains in the north-central Tarim Basin. This region is a typical fan-shaped plain oasis with terrain sloping from north to south and from northwest to southeast. The maximum elevation is 4,550 m, and the minimum is 922 m. Located in a warm temperate zone, the climate is dry with scarce precipitation, hot summers, and dry cold winters. The annual and diurnal temperature variations are large, characterized by a warm temperate continental arid climate. The average annual temperature ranges from 10.5 to 11.4°C, and annual precipitation ranges from 43.1 to 51.6 mm, placing it in arid and extremely arid zones. The study area and sample point distribution are shown in [Figure 1: see original paper].

1.2 Cotton Sample Collection and Chlorophyll Content Measurement Cotton sample data were collected on [date missing] in agricultural cotton fields in Akosutang Township, Kuqa City, Aksu Prefecture. The total cotton field area was 0.5 hm^2, with the cotton variety being Xinluzao [number missing]. The cotton was at the seedling stage, and [number missing] samples were collected. Sample point distribution is shown in [Figure 1: see original paper]. Planting followed local practices with 70 cm row spacing and 10 cm plant spacing under plastic film mulching ridges. Fertilization and cultivation management were conducted according to local planting requirements.

Chlorophyll content was measured using a SPAD-502Plus chlorophyll meter simultaneously with hyperspectral data acquisition. The SPAD-502Plus readings have a close relationship with chlorophyll content and can be used to estimate chlorophyll content [citation missing]. Therefore, this study treats SPAD values as equivalent to chlorophyll content for research purposes. Three leaves (upper, middle, and lower) were measured at each sample point, with [number missing] measurements per leaf taken at different positions, and the average value was used as the final value.

1.3 Spectral Data Collection and Processing Cotton canopy spectral reflectance was measured using an ASD FieldSpec HandHeld portable spectrometer with a detection wavelength range of 325–1,075 nm and spectral resolution of [value missing]. Measurements were taken between 11:30–15:30 Beijing time under windless, cloudless conditions. Whiteboard calibration was performed before measurement. The distance between the cotton canopy and spectrometer probe was 25 cm, with vertical orientation and a 25° field of view. Each sampling point was measured [number missing] times, with whiteboard calibration performed after every [number missing] measurements. The average of [number missing] curves calculated in ViewSpec Pro software was used as the spectral reflectance value for each sampling point.

This study applied several transformations to the original band spectral reflectance (R): logarithmic transformation (Log(R)), square root transformation ($\sqrt{R}$), continuum removal (CR), fractional-order differential transformation (FD), and continuous wavelet transformation (CWT). Traditional logarithmic and square root transformations enhance spectral differences in the visible light region, making absorption and reflection features more prominent. Continuum removal suppresses background spectra and expands weak absorption feature information [citation missing]. Fractional-order differential transformation increases sensitive bands and improves correlation coefficients [citation missing]. Continuous wavelet transformation can extract hidden effective spectral information, enhance spectral features, and strengthen correlations [citation missing].

1.4 Vegetation Index Extraction Based on previous studies [citation missing], we selected [number missing] vegetation indices widely applied in crop chlorophyll content research as parameters for the chlorophyll content inversion model, as shown in .

1.5 Model Construction and Evaluation This study used support vector regression (SVR) and random forest regression (RFR) models for modeling [citation missing], comparing their performance. The Whale Optimization Algorithm (WOA) was employed to optimize the [model name missing] model, testing the optimization effect and ultimately selecting the model with the best performance. Samples were divided into two groups: a modeling set (n = [number missing]) for model establishment and a validation set (n = [number missing]) for model validation.

Model accuracy was evaluated using three metrics: coefficient of determination (R^2), root mean square error (RMSE), and mean relative error (MRE) [citation missing]. Smaller errors and R^2 values closer to 1 indicate better model fit.

The Whale Optimization Algorithm, proposed in 2016, is a novel intelligent optimization algorithm inspired by the hunting behavior of humpback whale groups, which achieve optimization through searching, encircling, pursuing, and attacking prey [citation missing]. The algorithm's equations and principles are as follows:

The update method for the optimal path is:
$X(t+1) = X(t) - A \cdot |C \cdot X^*(t) - X(t)|$

Where X^* represents the coordinates of the optimal solution, X is the current solution coordinate, and coefficient vectors A and C are random vectors in [0,1].

The mathematical formula for searching prey is:
$X(t+1) = X_{rand} - A \cdot |C \cdot X_{rand} - X(t)|$

The spiral attack method is:
$X(t+1) = |X(t) - X(t)| \cdot e^{bl} \cdot \cos(2\pi l) + X(t)$

When humpback whales discover prey, they encircle or spiral attack based on selection probability p. The specific hunting behavior is determined by p: when $p < 0.5$, encircling predation occurs according to formula (1); when $p \geq 0.5$, spiral attack occurs according to formula (2).

By continuously updating X(t) through this movement and iterating until the optimal individual is obtained.

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2. Results

2.1 Statistical Analysis of Cotton Leaf Chlorophyll Content and Spectral Characteristics The average chlorophyll content values in the modeling and validation sets were [values missing], with standard deviations of [values missing] and coefficients of variation of [values missing]. The average value for all samples was [value missing], with a standard deviation of [value missing] and coefficient of variation of [value missing]. All dataset variation coefficients were less than [value missing], indicating low data variability (see [Figure 2: see original paper]).

To analyze the response characteristics between cotton leaf chlorophyll content and spectral reflectance, we calculated the maximum, minimum, average, and median chlorophyll content values for all samples and studied the original spectral reflectance under different chlorophyll content levels (see [Figure 3: see original paper]). Although the spectral curves of samples with different chlorophyll content were generally similar, certain differences existed. In the visible light band range of 325–680 nm, reflectance showed a negative correlation with chlorophyll content, reaching the highest correlation (r = [value missing]) at [wavelength missing]. In the 900–1,000 nm range, reflectance showed a positive correlation, with the highest correlation coefficient reaching r = [value missing] at [wavelength missing].

Within the 600–700 nm range, a reflectance valley formed near 690 nm, while an absorption valley formed near 550 nm. In the 700–750 nm range, reflectance gradually decreased, then gradually increased up to 800 nm. In the 950–975 nm band range, lower chlorophyll content corresponded to higher reflectance, confirming that cotton leaf chlorophyll content significantly affects the visible light band.

Comparing different mathematical spectral transformation methods, logarithmic transformation and continuum removal transformation did not improve correlation coefficients across the full band, with correlations lower than the original spectrum. Fractional-order transformation (using FD-1.3 as an example) showed correlations of -0.41 in 600–700 nm and 0.34 in 800–900 nm. Wavelet transformation (using CWT-7 as an example) showed correlations of -0.30 in 600–700 nm and 0.41 in 800–900 nm. These results indicate that fractional differential transformation and wavelet transformation are better preprocessing methods.

2.2 Vegetation Index Combination and Screening As shown in [Figure 5: see original paper], vegetation indices were calculated based on original spectra, continuum removal, fractional-order transformations (with step size [value missing]), and wavelet transformations (scale [value missing]). Vegetation indices passing the [significance level missing] correlation significance test were selected as combination vegetation indices.

On original spectral data, only [number missing] vegetation indices passed the [significance level missing] correlation significance level. In contrast, traditional mathematical transformations (logarithmic transformation), fractional-order transformations, and wavelet transformations (scale 7) each had over [number missing] vegetation indices passing the significance level. These mathematical transformations improved the correlation between more vegetation indices and cotton leaf chlorophyll content. Vegetation indices from these transformations were ranked by correlation coefficient magnitude, and the top [number missing] indices with highest correlation were selected as combination vegetation indices for further analysis.

On square root transformation, continuum removal, fractional-order [order missing], and wavelet transformation scale [value missing], fewer than [number missing] vegetation indices passed the [significance level missing] significance test, so no further analysis was conducted.

2.3 Correlation Analysis of Multi-Vegetation Index Combinations presents the correlation statistics between vegetation indices and cotton chlorophyll content under different spectral transformations. Correlation analysis was conducted between vegetation indices and cotton leaf chlorophyll content for each transformation. All vegetation index correlations under original spectra were lower than those under transformed spectra, demonstrating that mathematical transformations of spectral data can improve correlations between vegetation indices and chlorophyll content.

Under fractional-order [order missing] transformation, vegetation index correlations ranged from -0.31 to 0.34. Under wavelet transformation scale [value missing], correlations ranged from -0.33 to [value missing]. Fractional-order transformation and wavelet transformation were more effective at improving correlations between chlorophyll content and vegetation indices.

2.4 Modeling Results and Analysis Using multiple spectral preprocessing methods and different vegetation index combinations, we established [model name missing] models to estimate cotton leaf chlorophyll content, investigating the impact of different vegetation index combination methods on model accuracy. Results are shown in .

The [model name missing] model performed well across different mathematical transformations, demonstrating the feasibility of [method missing]. The [model name missing] model showed relatively poor inversion performance, with large accuracy differences between modeling and validation sets, indicating that this model is significantly affected by sample size and has poor stability.

Based on logarithmic transformation multi-vegetation index combinations, the [model name missing] model achieved training set R^2 of [value missing] and validation set R^2 of [value missing], higher than other [model type missing] models. In fractional-order transformations, the [model name missing] model achieved training set R^2 of [value missing] and validation set R^2 of [value missing], representing an improvement of [value missing] over the original spectral vegetation index model's R^2. In wavelet transformation scales, scale [value missing] achieved the highest training set R^2 ($R^2 = 0.934$).

Comprehensive analysis shows that the multi-vegetation index combination model based on fractional-order [order missing] transformation performed best, with high R^2 values and optimal modeling performance, enabling relatively accurate estimation of cotton leaf chlorophyll content.

Scatter plots of measured versus predicted values (see [Figure 6: see original paper]) show that for different mathematical transformations, validation set predictions were better than modeling set predictions. The model based on fractional-order [order missing] combined vegetation indices showed good predictive performance, with most data points distributed closely around the fitted line.

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3. Discussion

Data transformation methods can improve the correlation between vegetation indices and chlorophyll content, consistent with previous research. Tong et al. [citation missing] demonstrated in their study on pasture aboveground biomass estimation using different-order differential hyperspectral vegetation indices that differential processing of original hyperspectral reflectance helps correlate spectral data with aboveground biomass. Li et al. [citation missing] concluded from their study on hyperspectral quantitative inversion of pitaya stem chlorophyll content that mathematical transformations and continuous wavelet transformation significantly improved spectral estimation capability. Jing et al. [citation missing] improved the correlation between spectral reflectance and wheat stripe rust severity through fractional-order differential processing of original spectra in their research on wheat stripe rust remote sensing monitoring models.

Additionally, this study shows that model accuracy for cotton leaf chlorophyll content constructed using multiple vegetation index combinations is higher than in other studies. The WOA-RFR model based on fractional-order 0.9 transformation and Vogelmann3, RVI, DVI, SR[675-700], Mndvi705, ND, VOG1, NVI, TVI, VOG2 combined vegetation indices achieved R^2 values of 0.920 and 0.955 for training and validation sets, respectively, with RMSE of 0.987 and 0.986, and MRE of 0.013 and 0.014. This demonstrates the feasibility of hyperspectral vegetation indices composed of specific band reflectance for chlorophyll content inversion. Xu et al. [citation missing] studied canopy nitrogen content inversion methods based on multi-vegetation index combinations, establishing ELM models with 12 different input combinations that all showed good performance. The best model used 10 vegetation indices as input, achieving training and validation R^2 of [values missing], superior to single vegetation index models.

However, this study only investigated leaf chlorophyll content at the cotton seedling stage. Chlorophyll content varies with different growth periods and changes with crop development. Therefore, future research should strengthen model application across different growth periods. The applicability of vegetation indices differs among crop types and growth stages, affecting chlorophyll estimation capability. Thus, future studies should optimize vegetation indices and further explore their potential in chlorophyll content inversion research.

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4. Conclusion

(1) All original spectral transformations improved the correlation between chlorophyll content and vegetation indices. Traditional transformations showed highest correlation with logarithmic transformation, fractional-order transformation at order 0.9, and wavelet transformation at scale 7. In this study, fractional-order transformation improved correlations more than wavelet transformation.

(2) Inversion models based on different vegetation index combinations under various spectral transformations performed well, all achieving $R^2 >$ [value missing]. The WOA-RFR model based on fractional-order 0.9 transformation with Vogelmann3, RVI, DVI, SR[675-700], Mndvi705, ND, VOG1, NVI, TVI, VOG2 vegetation index combination achieved the best performance, with modeling and validation set R^2 of 0.920 and 0.955, respectively.

(3) Among all inversion models, WOA optimization showed significant improvement for fractional-order transformed vegetation index combinations, with R^2 increasing by at least [value missing] for each spectral transformation. The Whale Optimization Algorithm demonstrated notable optimization effects, particularly for random forest regression models.

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Note: Figure translations are in progress. See original paper for figures.