IEEE Access
Multidisciplinary | Rapid Review | Open Access Journal

Received 1 July 2023, accepted 13 July 2023, date of publication 20 July 2023, date of current version 25 July 2023.

Digital Object Identifier 10.1109/ACCESS.2023.3296635

RESEARCH ARTICLE

A Study on the Estimation Model of Hyperspectral Reflectivity and Leaf Nitrogen Content of Cotton Leaves

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This work was supported in part by the Oasis Ecological Agriculture Corps Key Laboratory Open Project under Grant 202002; in part by the National Natural Science Foundation of China under Grant 61563046 and Grant 61961035; in part by the Corps Science and Technology Program under Grant 2021CB041, Grant 2021BB023, and Grant 2021DB001; and in part by the Tarim University Innovation Team Project under Grant TDZKCX202306 and Grant TDZKCX202102.

ABSTRACT Modern agriculture requires more accurate field management capability compared with traditional agriculture. The development of hyperspectral remote sensing technology embodies rapid and non-destructive features in agricultural information monitoring, providing a technical guarantee for the scientific management of agricultural production. The mathematical model of inverse cotton leaf total nitrogen was established by decomposing and transforming the original cotton leaf spectrum using continuous wavelet analysis and traditional spectral transformation, taking the characteristic wavelet coefficients and spectral characteristic bands as independent variables, and using univariate, stepwise regression, and partial least squares methods. The correlation between the total nitrogen content of cotton leaves and the spectral reflectance, through different methods of spectral treatment, was improved to different degrees. For the conventional spectral transformation, the inverse logarithmic first-order differential $\lg'(1/R)$ improved the correlation of cotton leaf total nitrogen by 0.26. The continuous wavelet analysis outperformed the conventional spectral model regarding information noise reduction and mining of feature information. The established model with RPD>2 had good stability and predictive power for all sample data.

INDEX TERMS Hyperspectral, non destructive testing, continuous wavelet analysis, spectral transformation, total nitrogen, cotton.

I. INTRODUCTION

Agricultural production requires large amounts of mineral nutrients such as nitrogen, phosphorus, and potassium to meet the needs of crop growth. Cotton, as the main cash crop in Xinjiang, accounts for 80% of the national production value and plays a pivotal role in the economic and social development of Xinjiang. In cotton cultivation, nitrogen is of great importance for cotton growth and is considered to be an important factor in biomass production in addition to water [1], [2], [3] with carbohydrates for synthesis of proteins, chlorophyll and other nitrogenous compounds. In related studies, it was found that the increase of nitrogen, within a certain range, has a positive effect on the growth condition and yield quality of cotton, and once too much nitrogen fertilizer is used, it will not only lead to a reduction in its yield quality, but also cause damage and pollution to the soil and groundwater resources because of the leaching effect [4], in response to the problems of high nitrogen fertilizer input and low fertilizer utilization over the years, the cotton growing process how to better apply nitrogen fertilizer To improve the yield and quality of cotton, but also to prevent the ecological damage and pollution caused by excessive application of nitrogen fertilizer, it is especially important to

The associate editor coordinating the review of this manuscript and approving it for publication was John Xun Yang.

obtain the nitrogen content of cotton during growth in a timely and accurate manner.

From the 1960s to 1970s, the USDA developed a simple empirical statistical model for leaf scale using more than 40 characteristic bands of biochemical components of dried leaves, and estimated biochemical parameters such as leaf protein and lignin by means of satellite remote sensing in the late 1980s, and obtained results in general agreement with indoor tests. At present, with the development of the application technology and processing means of spectroscopy, the research results about hyperspectral in agriculture are increasing, and researchers have used satellite, unmanned aircraft and handheld hyperspectral equipment to establish high level prediction models not only for nutrient elements and chlorophyll of maize [5], wheat [6], [7], rice [8] and cotton [9], [10], but also for crop identification [11], [12] and Zhao et al. [13] used vegetation indices with near-infrared spectral reflectance to assess the potential of nitrogen content monitoring and identification of cotton canopies at the growth stage, and Plant et al. [14] investigated whether normalized difference vegetation indices (NDVI) could provide valid information for cotton in specific regions, concluding that relative nitrogen vegetation indices, used as indicators of nitrogen N stress indicators when its performance is lower than NDVI. The above studies demonstrate the feasibility of analyzing crop nutrient composition by spectroscopic techniques.

Because satellites and UAVs have the limitations of high cost and high technical operation [15], this experiment uses near-ground hyperspectral, handheld hyperspectrometer, which not only reduces the technical operation but also avoids clouds and reduces the influence of atmospheric environment, obtains high spatial resolution, identifies fine-scale features, and thus greatly improves the acquisition of crop growth information. Since the raw spectral reflectance is subject to background noise such as atmosphere and light as well as interference from adjacent bands, processing and transformation of hyperspectral data can uncover hidden feature information and reduce background interference and data redundancy. Various models using mathematical analysis to transform hyperspectral reflectance have been developed in studies of nitrogen and chlorophyll prediction in vegetation crops [16], [17]. Wavelet analysis is equivalent to a mathematical microscope and telescope with multi-scale analysis with multiple resolutions and directional changes, and has made developments in the monitoring of crop chlorophyll content prediction, heavy metal elements and physiological information and pests and diseases [18], [19], [20], [21], [22].

In this study, the raw spectra were processed using continuous wavelet analysis and conventional spectral transform, and the models developed by these two methods were analyzed and compared for their ability to estimate the total nitrogen content of cotton leaves, and secondly, the contributions of univariate analysis, stepwise regression analysis, and partial least squares to model accuracy and stability were analyzed and compared.

II. EXPERIMENTAL AREA OVERVIEW, DATA SOURCES AND RESEARCH METHODS

A. OVERVIEW OF THE STUDY AREA

The experiment was conducted in June and October 2021 at the Horticultural Experiment Station of Tarim University, which is located in Alar City, Xinjiang Uygur Autonomous Region, which has a temperate continental climate from the southern foothills of the Tianshan Mountains in the north to the northern edge of the Taklamakan Desert in the south, with an annual cotton cultivation area of 155.0 thousand hectares. Four nitrogen fertilizer gradient treatments of 0 (N0), 100 (N1), 200 (N2) and 300 kg/hm^2 (N3) were set up, with three replications for each treatment, and a total of 24 plot trials were set up. The potassium fertilizer applied to cotton cultivation is mainly potassium sulfate (K_2O content of about 50%) which is expensive and low in nutrient content, but the long-term application of potassium sulfate to the soil in this test area is prone to the formation of calcium sulfate (gypsum) precipitation in the cultivated soil layer, leading to soil caking. Although potassium chloride is inexpensive and has a high nutrient content (K_2O content of about 60%), it cannot meet the field crop situation. Garlic (onion, pepper, shallot, etc.) crop with cotton is sensitive to chlorine, and high chloride content in the soil will reduce the crop quality.

Cotton leaves were collected on June 15 (bud stage) and October 1 (spat stage), and a relatively regular rectangular cotton field, 40 m long from east to west and 60 m long from north to south, was selected in the horticultural station using a five-point sampling method. A total of five sampling points were selected at the four corners and the center, and five cotton plants were selected at each sampling point to collect hyperspectral data and the corresponding total nitrogen content of the leaves of different cotton at different locations according to four directions: east, south, west, and north. The representative cotton leaves were collected and the average of five measurements was used as the original spectral data of the sampled leaves. The collected cotton leaves were temporarily stored in sealed bags and brought to the laboratory as soon as possible to determine the nitrogen content, and a total of 125 sets of hyperspectral reflectance and total nitrogen content data were obtained for the five sampling sites.

B. TEST DATA ACQUISITION

1) SPECTRAL REFLECTANCE MEASUREMENT

Leaf spectral data were measured using an ASD portable geophysical spectrometer with a wavelength range of 325∼1075 nm and a spectral sampling interval of 1 nm. Calibration tests were performed on a white board before use, and calibration was performed again after each leaf measurement to eliminate instrument errors to the maximum extent. The cotton leaf spectral data collection was carried out in clear weather with no wind or breeze conditions selected at 10:00-14:00, and calibration will be performed every 10 min due to the change of sun position. Hand-held spectrometer, sensor vertical downward, probe angle of 25°, uniformly

TABLE 1. Test equipment.

Instruments	Model	Manufacturers
ASD Portable Geospectrometer	FieldSpec HandHeld 2	Beijing Liga United Technology Co
FOSS Automatic Kjeldahl Nitrogen Detector	KJELTECTM8400	FOSS China (Beijing) Technology Co
Analytical scales	HY-5	Jintan City Medical Equipment Factory
Digital display blast dryer	GZX-9410MBE	Shanghai Boxun Industrial Co
FOSSD igestive ovens	Digestor 2520	FOSS China (Beijing) Technology Co

TABLE 2. Test reagents.

Reagent	Molecular formula	Purity	Manufacturers
Sodium hydroxide	$NaOH$	Analysis pure (AR)	Tianjin Zhiyuan Chemical Reagent Co
Concentrated sulphuric acid	H_2SO_4	Analysis pure (AR)	Sichuan Xilong Chemical Co
Sodium carbonate anhydrous	Na2CO3	Analysis pure (AR)	Tianjin Zhiyuan Chemical Reagent Co
Hydrochloric acid	HCl	Analysis pure (AR)	Sichuan Xilong Chemical Co
Methyl Red	$C_{15}H_{15}N_3O_2$	Analysis pure (AR)	Tianjin Tianxin Fine Chemical Development Centre
Bromocresol Green	$C_{21}H_{14}Br_4O_5S$	Analysis pure (AR)	Tianjin Damao Chemical Reagent Factory
Anhydrous ethanol	C_2H_5OH	Analysis pure (AR)	Tianjin Yongda Chemical Reagent Co
Boric acid	H_3BO_3	Analysis pure (AR)	Tianjin Zhiyuan Chemical Reagent Co
Catalysts	K_2SO_4, $CuSO_4 \bullet 5H_2O$	Analysis pure (AR)	Beijing Jinyuan Xingke Technology Co

select representative cotton leaves each time 10 measurements, take the average of 10 spectral data as the leaf spectral data.

2) MEASUREMENT OF LEAF NITROGEN CONTENT

The total nitrogen content of cotton leaves was determined using a FOSS automatic Kjeldahl nitrogen tester, which is based on the principle of converting organic nitrogen in leaves into ammonium sulfate in a series of reactions under the action of concentrated sulfuric acid and efficient catalysts, and then distilled using sodium hydroxide solution to determine the total nitrogen content of leaves. Three leaves from each test plot were selected and killed at 105°C for 30 min in a drying oven, then dried at 80°C to constant weight [23], and after cooling, the leaves were fully ground to a uniform powder using a mortar and pestle; the samples were accurately weighed into a decoction tube using an electronic balance with one-ten-thousandth accuracy, then 10 mL of concentrated sulfuric acid and a catalyst were added, and then digested on a FOSS digestion oven The nitrogen content was calculated automatically according to the volume of hydrochloric acid standard solution used, and the average value of the nitrogen content of the three leaves was taken as the nitrogen content of the test plot.

3) CONTINUOUS WAVELET ANALYSIS

In the process of cotton vegetation growth, various biochemical parameters within cotton have different effects on the reflectance spectra of different wavelengths, which are reflected in the spectra as continuous "peaks" and "valleys" at different locations. "The concept of wavelet variation was pioneered by a French researcher. The concept of wavelet variation was first introduced by French engineer Morlet in oil exploration, using continuous wavelet variation to find the characteristic absorption of various biochemical parameters hidden in the spectral reflectance. As one of the most effective methods in the field of signal processing, the continuous wavelet transform method has been applied extensively to extract biochemical parameters and leaf area indices, including leaf hyperspectra and ground hyperspectra [24], [25], [26], [27]. Compared with the traditional vegetation indices based on several wavebands, the continuous wavelet analysis method can obtain the absorption characteristics of biochemical parameters and the effect of amplitude of leaf area index on reflectance from hyperspectral remote sensing data by using the multi-scale decomposition property.

The continuous wavelet transform of the reflectance spectrum is to obtain wavelet coefficients by convolving the reflectance spectrum with the mother wavelet function of translation and scaling.

$$\varphi_{a,b}(\lambda) = \frac{1}{\sqrt{a}}\varphi\left(\frac{\lambda - b}{a}\right) \tag{1}$$

$$w_f(a, b) = \int_{-\infty}^{+\infty} f(\lambda)\varphi_{a,b}(\lambda)d\lambda \tag{2}$$

where $\varphi(\lambda)$ is the mother wavelet function, $\varphi_{a,b}(\lambda)$ is the mother wavelet function after translation and scaling, a is the scaling factor, which can also be called the scale, and b is the translation factor, and the band position. $w_f(a, b)$ is the wavelet coefficient (characteristic wavelet), which can be seen as the similarity of the wavelet mother function to the reflectance data at the scale a and b bands.

In this paper, we will use Mexican Hat wavelet as the mother function of continuous wavelet transform, which is essentially the second-order derivative function of Gaussian function with the following equation:

$$\varphi(x) = \frac{2}{\sqrt{3}}\pi^{\frac{-1}{4}}(1 - x^2)e^{-\frac{x^2}{2}} \tag{3}$$

$$\int_{-\infty}^{+\infty} \varphi(x)\, d(x) = 0 \tag{4}$$

The Gaussian second-order derivative function is similar to the shape of the reflection peak and reflection valley of the reflection spectrum, so it can be well optimized locally and can effectively remove part of the interference of environmental noise and play a better smoothing role.

4) TRADITIONAL SPECTRAL TRANSFORMATION

The differential technique, inverse logarithmic transformation is one of the common hyperspectral data processing methods, which can reduce the interference caused by background noise and instrumental factors such as atmosphere and illumination, and also improve the clarity of the original spectral reflectance curve, and some obscure characteristic peaks will be resolved to show the information that can be monitored compared with the original spectrum [28]. Among them, first-order differential spectroscopy and first-order inverse logarithmic differencing can extract different sensitive spectral parameters to better reflect the characteristics of the plant itself. The inverse logarithm can amplify the spectral differences in the visible region and transform part of the spectral data from a nonlinear to a linear relationship. In this study, the smoothed spectral values are transformed by inverse logarithmic, first-order differencing and first-order inverse logarithmic differentiation, which are calculated as follows.

$$\mathrm{R}'_{\lambda} = \frac{R_{\lambda+1} - R_{\lambda-1}}{2\Delta\lambda} \tag{5}$$

$$\lg'\left(\frac{1}{R_\lambda}\right) = \frac{\lg(\frac{1}{R_{\lambda+1}}) - \lg(\frac{1}{R_{\lambda-1}})}{2\Delta\lambda} \tag{6}$$

where R'_{λ} is the first-order differential value at wavelength λ, $\mathrm{R}_{\lambda+1}$ and $\mathrm{R}_{\lambda-1}$ are the spectral reflectance values at wavelengths $\lambda + 1$ and $\lambda - 1$, respectively; is the first-order differential value of the inverse logarithm at wavelength λ, and and is the inverse logarithm value at wavelengths $\lambda + 1$ and $\lambda - 1$, respectively.

5) MODELING METHODS

a: SINGLE INDEPENDENT VARIABLE REGRESSION ANALYSIS MODEL

The univariate regression analysis is to establish a functional relationship between y and x by directly finding the correlation between y and x. In addition to the linear function, another second-order polynomial function is selected for fitting in this paper. Second-order polynomial fitting is done by fitting a quadratic function to the data to obtain a more accurate functional model of the general form $y =$ ax^2+bx+c, where a, b, and c are the coefficients to be solved for. When performing a second-order polynomial fit, we need to process the data first and then use least squares to solve for the coefficients.

b: STEPWISE REGRESSION ANALYSIS MODEL

Stepwise regression analysis (SR) is a kind of multiple linear regression analysis, which establishes the optimal regression equation by selecting the independent variables and mainly solves the multivariate covariance problem. The process is to introduce the independent variables with significant effects into the regression equation one by one according to their effects on the dependent variable, while those with insignificant effects on the dependent variable are chosen to be ignored. When new variables are introduced, the effects of the ignored variables on the original regression equation may change, and if they become significant, they are reintroduced into the regression equation until Therefore, the stepwise regression analysis combines the forward introduction method and the backward elimination method.

c: PARTIAL LEAST SQUARES REGRESSION ANALYSIS MODEL

Partial least squares regression analysis (PLSR) is a regression modeling method to study multiple dependent variables or single dependent variables on multiple independent variables, including three basic analysis methods using multiple linear regression analysis, principal component analysis and typical correlation analysis, combining their advantages to enable regression modeling in the presence of severe multiple correlations in the independent variables, effectively solving the problem of self-model co-linearity, and its regression model has a strong stability [29].

6) MODEL EVALUATION INDEXES

To indicate the goodness of fit and prediction accuracy of the regression model, the coefficient of determination (R2), root mean square error (RMSE), and relative analytical error (RPD) were selected to evaluate the chlorophyll and total nitrogen inversion models in this paper. There are three levels of RPD for model evaluation, when RPD $<$ 1.4, it means that the regression model has the worst accuracy and cannot make effective prediction of sample data; when $1.4 \leq RPD < 2$, it means that the regression model has average accuracy and can make rough prediction of sample data; when $RPD \geq 2$ when $RPD \geq 2$, it means that the accuracy of the regression model is good and can make effective prediction of the sample data.

III. RESULTS AND ANALYSIS

A. COTTON LEAF TOTAL NITROGEN INVERSION ESTIMATION

1) SPECTRAL REFLECTANCE MEASUREMENT

A total of 200 samples of cotton leaf total nitrogen were collected at the bud stage in June and the flocculation stage in October, and 30% of the samples were randomly selected as the validation set and 70% as the modeling set. The distribution and statistics of chlorophyll data are shown in Figure 1 and Table 3, and it can be seen from the graphs that the range of variation and coefficient of variation of the three groups of leaf total nitrogen samples did not vary much, and the normal curve data were evenly distributed, and there was no significant difference between the three groups of samples by single-factor analysis, which in summary indicates that the modeling set validation set is reasonably divided and suitable for modeling and validation.

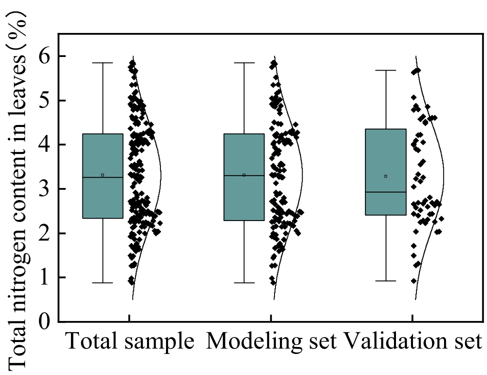

FIGURE 1. Distribution of leaf total nitrogen sample data.

TABLE 3. Statistical table of leaf total nitrogen sample data.

Data name	Sample size	Minimum value	Maximum value	Average	Standard deviation	Variance	Coefficient of variation /%
Total sample	200	0.8851	5.8522	3.3059	1.1995	1.4389	36.28
Modeling set	140	0.8851	5.8522	3.3151	1.2066	1.4559	36.40
Validation set	60	0.9229	5.6777	3.2846	1.1927	1.4225	36.31

Note: Leaf nitrogen content unit is %

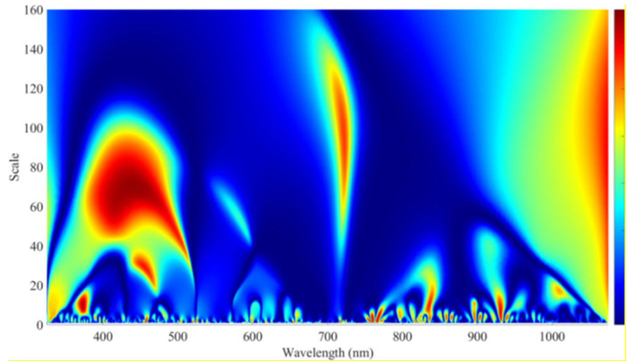

FIGURE 2. R2 distribution of total nitrogen wavelet coefficient sensitivity in cotton leaves.

By subjecting 200 sets of spectral data collected in 2021 to mexh continuous wavelet analysis at scales a=1 to 160, wavelet coefficients at different scales and bands were obtained, and the calculated wavelet coefficients were correlated with the measured values in turn, and finally the distribution of wavelet coefficient sensitivity R2 of cotton leaf total nitrogen was obtained, as shown in Figure 2.

To determine the characteristic wavelet coefficients of total nitrogen in cotton leaves more accurately and reasonably, and to establish a better fitting and more accurate and stable inversion model, the wavelet characteristic coefficients of leaf chlorophyll need to exclude the common sensitive area of leaf chlorophyll and leaf nitrogen content for this selection. To exclude the common sensitive area as the principle, the 10 wavelet coefficients with the largest correlation were selected for comparative analysis, and the average value of the determination coefficient of the selected 10 wavelet coefficients was 0.6543.

3.1.3. Correlation analysis of total nitrogen in cotton leaves by conventional spectral transformation.

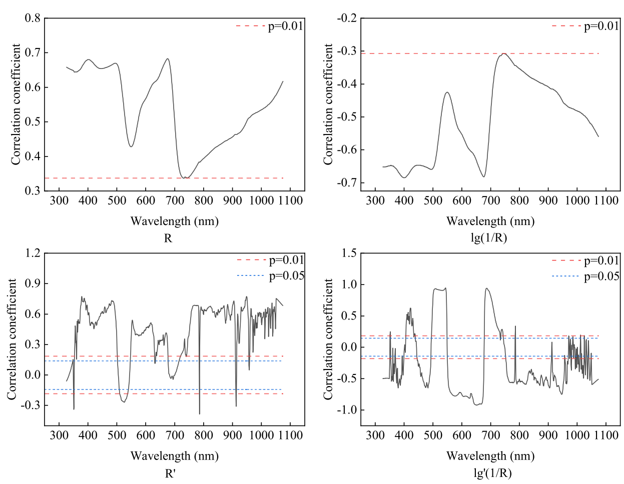

FIGURE 3. Distribution of correlation coefficients between spectral transformations and total leaf nitrogen.

After the Savitzky-Golay convolution smoothing of the original spectra, the first-order differentiation, inverse logarithmic, and first-order inverse logarithmic differentiation processes were then performed to establish the correlation analysis between the obtained different spectral values and the total nitrogen content of cotton leaves, and the results are shown in Figure 3.

Figure 3 reflects the correlation between the total nitrogen content of cotton leaves and the spectral values obtained from the spectral transformations of different methods. From the figure, the total nitrogen of cotton leaves almost positively correlated with the original spectral reflectance, which is consistent with the results of the Yierxiati experiment [16]; the logarithm of the reciprocal almost negatively correlated with the total nitrogen content, with correlation coefficients between −0.307 and −0.682, reaching a highly significant level; the first-order differential and the logarithm of the reciprocal first-order differential correlations alternated positively and negatively, with large curve fluctuations. The maximum correlation between raw spectral reflectance and inverse log spectral values appeared at 674 nm and 678 nm with correlation coefficients of 0.682 and −0.682, respectively; the maximum correlation between first-order differentiation and inverse log first-order differentiation appeared at 379 nm and 686 nm with correlation coefficients of 0.774 and 0.94, respectively. Different forms of mathematical transformations had different effects on the correlation between raw spectral reflectance and total nitrogen of cotton leaves. The difference between the logarithmic transformation on the correlation of cotton leaf total nitrogen content and the original spectrum did not change much, while the correlations of both first-order differential and logarithmic first-order differential were significantly improved, and the maximum correlation wavelengths also changed differently, making the maximum correlation wavelengths relatively concentrated.

In the above figure of the four method treatments, we can find the location of the wave peak in the region around 550 nm, and Buscaglia et al. concluded that the spectral reflectance at 550 nm is closely related to the nitrogen concentration of cotton leaves [30], in addition to the conclusion that can be drawn from the figure, the characteristic wavelengths related to the nitrogen content are mainly located in the red edge region (670-760 nm) In addition, Clevers suggested that the red-edge region could be used to estimate chlorophyll and nitrogen content [31]. Wood et al. studied an experiment using handheld chlorophyll to determine the nitrogen content of cotton leaves and found a correlation between chlorophyll and nitrogen content. In addition, Shankar and Gupta [32]used a chlorophyll meter to predict the nitrogen content of Bt cotton and showed that the chlorophyll meter could effectively quantify the nitrogen content of Bt cotton during the first Gitelson et al. suggested a high sensitivity to chlorophyll around 540-630 nm and 700 nm [33], and Curran suggested that 460 and 640 nm are sensitive to chlorophyll b while 660 nm is sensitive to chlorophyll a [34], thus suggesting that leaf nitrogen content in the above-mentioned regional range correlates well with spectral There is a large correlation between leaf nitrogen content and spectral reflectance in the above-mentioned region.

Modeling of hyperspectral inversion of total nitrogen in cotton leaves

a: UNIVARIATE REGRESSION ANALYSIS MODEL

The univariate regression model was constructed by using the characteristic wavelet coefficients obtained by wavelet analysis, the original spectral reflectance, and the spectral parameters of the three traditional spectral transformations as independent variables and the total nitrogen of cotton leaves as dependent variables. The modeling and validation results are shown in Table 4.

As can be seen from Table 4, different forms of spectral treatments equally enhanced the correlation and inverse model accuracy of spectral reflectance with total nitrogen in cotton leaves to different degrees. The univariate model with the original spectral rate and the inverse logarithm as independent variables had the smallest coefficient of determination R2, and the model prediction was average; for the first-order differential and the inverse logarithm first-order differential $\lg'(1/R)$ transformed model established after the coefficient of determination R2 was significantly improved compared with the former, but its RPD was still less than 2, so the model prediction ability was average. The models with characteristic wavelet coefficients as independent variables obtained from CWT, in the modeling set, the R2 are between 0.6378∼0.7086, and the RMSE are between 0.6200∼0.6912, with little overall variation but the second-order polynomial model is obviously better than the linear model; in the validation set, the R2 of the models are between 0.5489∼0.6593, and the RPD are in 1.452∼1.720, thus indicating that the univariate regression models established by CWT could not make effective predictions for the sample data and could only be used for rough predictions of the inverse model.

From the above analysis, there may be the following reasons for the poor accuracy of the cotton nitrogen inversion model: first, there are problems with the experimental measurement of leaf total nitrogen operation, resulting in errors between the measured and true values; second, the complete spectral range was not used in this study in this paper, and it can be seen from the CWT and cotton leaf correlation coefficient graph that after the wavelength of 1200 nm, it may also have a wavelet coefficient that reaches a highly significant level. Clever argued that the spectra collected by remote sensing techniques are mainly used to obtain information on chlorophyll rather than directly on nitrogen content [35]. In general, raw spectral reflectance can provide useful information, but its function may be limited in some specific orders. Therefore, future research in this paper will focus on extracting the complete spectral range.

b: MULTIVARIATE REGRESSION ANALYSIS MODEL

The characteristic wavelet coefficients obtained by wavelet analysis as well as the spectral parameters of raw spectral

TABLE 4. Univariate regression model modelling and validation results.

Variable	Model	Regression equation	Modelling set R^2	Modelling set RMSE	Validation set R^2	Validation set RMSE	Validation set RPD
W_f (70,435)	Linear	y=13.332x+3.798	0.6674	0.6624	0.6289	0.6493	1.648
	Multiple	y=21.925x^2+15.128x+3.727	0.6839	0.6457	0.6527	0.6270	1.706
W_f (70,436)	Linear	y=13.363x+3.810	0.6683	0.6614	0.6292	0.6491	1.648
	Multiple	y=22.463x^2+15.251x+3.738	0.6855	0.6440	0.6534	0.6265	1.708
W_f (70,437)	Linear	y=13.398x+3.817	0.6690	0.6607	0.6291	0.6492	1.648
	Multiple	y=23.097x^2+15.377x+3.746	0.6870	0.6425	0.6538	0.6262	1.709
W_f (70,438)	Linear	y=13.445x+3.826	0.6696	0.6602	0.6290	0.6493	1.648
	Multiple	y=23.719x^2+15.512x+3.755	0.6883	0.6412	0.6540	0.6493	1.648
W_f (71,441)	Linear	y=13.709x+3.783	0.6836	0.6460	0.6392	0.6408	1.670
	Multiple	y=21.291x^2+15.315x+3.711	0.6982	0.6309	0.6588	0.6222	1.720
W_f (69,443)	Linear	y=13.739x+3.879	0.6710	0.6588	0.6264	0.6517	1.642
	Multiple	y=28.994x^2+16.589x+3.813	0.6967	0.6325	0.6549	0.6255	1.711
W_f (69,444)	Linear	y=13.814x+3.884	0.6723	0.6575	0.6269	0.6513	1.643
	Multiple	y=29.617x^2+16.743x+3.819	0.6987	0.6304	0.6552	0.6253	1.711
W_f (71,444)	Linear	y=13.961x+3.799	0.6879	0.6415	0.6405	0.6397	1.673
	Multiple	y=22.684x^2+15.707x+ 3.727	0.7036	0.6253	0.6593	0.6221	1.720
W_f (70,447)	Linear	y=14.242x+3.830	0.6888	0.6407	0.6391	0.6411	1.669
	Multiple	y=26.567x^2+16.456x+3.757	0.7086	0.6200	0.6593	0.6225	1.719
W_f (1,689)	Linear	y=1305.312x+3.659	0.6378	0.6912	0.5580	0.7107	1.505
	Multiple	y=504994.236x^2+1758.622x+3.504	0.7021	0.6268	0.5489	0.7370	1.452
R_{402}	Linear	y=22.324x+2.037	0.4625	0.8773	0.5492	0.7941	1.502
	Multiple	y=-86.579x^2+37.159x+1.588	0.4893	0.8551	0.5920	0.7555	1.579
R'_{379}	Linear	y=4140.961x+2.956	0.6002	0.7566	0.6442	0.7055	1.691
	Multiple	y=-1769950.87x^2+4673.47x+3.013	0.6081	0.7490	0.6556	0.6941	1.718

TABLE 4. *(Continued.)* Univariate regression model modelling and validation results.

Variable	Model	Regression equation	Modelling set R^2	Modelling set RMSE	Validation set R^2	Validation set RMSE	Validation set RPD
lg(1/R)$_{677}$	Linear	y=-2.463x+6.015	0.4645	0.8756	0.5316	0.8095	1.473
	Multiple	y=1.654x^2-6.412x+8.176	0.5015	0.8448	0.5764	0.7698	1.549
lg′(1/R)$_{687}$	Linear	y=175.386x+5.560	0.6295	0.7283	0.6504	0.7254	1.700
	Multiple	y=284.409x+4106.902x^2+6.162	0.6421	0.7158	0.6560	0.7205	1.711

reflectance and three conventional spectral transformations were used as independent variables and total nitrogen of cotton leaves was used as dependent variable to construct a model for estimating total nitrogen of cotton leaves by stepwise regression and partial least squares regression methods, respectively, and the modeling and validation results are shown in Table 5.

TABLE 5. Multivariate regression model modelling and validation results.

Regression model	Modelling set R2	Modelling set RMSE	Validation set R2	Validation set RMSE	Validation set RPD
CWT-SR	0.8410	0.4578	0.7640	0.5253	2.037
R-SR	0.4663	0.8741	0.5427	0.7999	1.491
R′-SR	0.6564	0.7014	0.6773	0.6718	1.775
lg(1/R)-SR	0.4696	0.8714	0.5650	0.7814	1.526
lg′(1/R)-SR	0.6746	0.6825	0.7026	0.6672	1.848
CWT-PLSR	0.6993	0.6297	0.6675	0.6140	1.743
R-PLSR	0.4750	0.8669	0.5556	0.7884	1.513
R′-PLSR	0.6287	0.7291	0.6442	0.7054	1.691
lg(1/R)-PLSR	0.4740	0.8678	0.5548	0.7892	1.511
lg′(1/R)-PLSR	0.6511	0.7068	0.7128	0.6598	1.868

By analyzing Table 5, it can be seen that the model established by stepwise regression analysis after CWT decomposition has better model superiority, smaller prediction bias, and RPD is greater than 2, which indicates that the model has a good prediction effect on the sample data.

C: COMPARATIVE ANALYSIS OF COTTON LEAF TOTAL NITROGEN REGRESSION MODELS

In order to analyze the differences between different modeling methods, the optimal model among different modeling methods was selected for comparative analysis. The results are shown in Table 6.

From the above Table 6, it can be seen that the stepwise regression analysis model has good applicability in the prediction of total nitrogen content of cotton leaves. In order to better present the results of the regression model, the linear results of the chlorophyll inversion model are shown in Figure 4.

TABLE 6. Regression model modelling and validation results.

Regression model	Modelling set		Validation set		
	R^2	RMSE	R^2	RMSE	RPD
W_f(71,444)	0.7036	0.6253	0.6593	0.6221	1.720
Lg′(1/R)$_{687}$	0.6421	0.7158	0.6560	0.7205	1.711
CWT-SR	0.8410	0.4578	0.7640	0.5253	2.037
lg′(1/R)-SR	0.6746	0.6825	0.7027	0.6672	1.848
CWT-PLSR	0.6993	0.6297	0.6675	0.6140	1.743
lg′(1/R)-PLSR	0.6511	0.7068	0.7129	0.6598	1.868

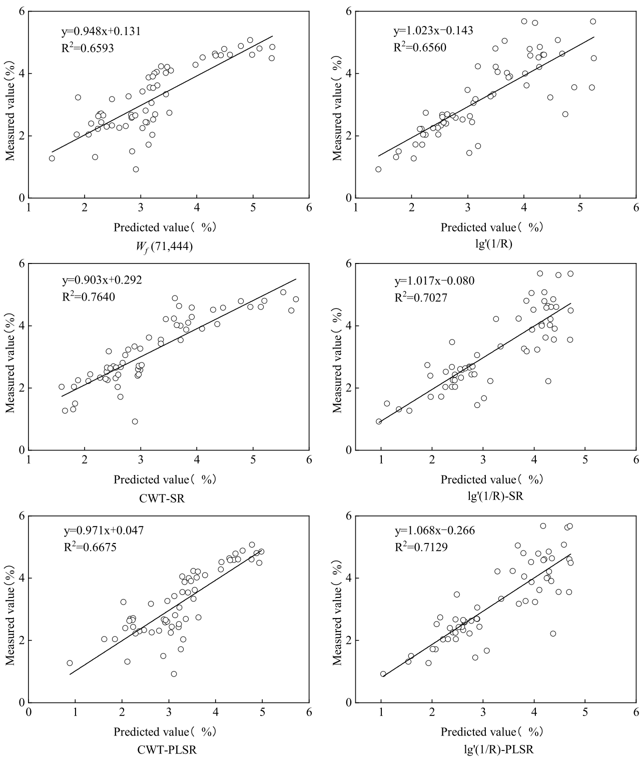

FIGURE 4. Results of a linear fit of the inverse model for total nitrogen in leaves.

IV. DISCUSSION

In this paper, a total of 200 sets of cotton leaf spectral data were collected from the Horticultural Experiment Station of Tarim University with a portable geophysical spectrometer, and cotton leaf total nitrogen was obtained by experimental means, and the continuous analysis of 200 sets of spectral data at 160 scales was performed by using the principle of Mexh wavelet analysis, and the original spectra were transformed by using traditional mathematical methods, and then the biochemical and biochemical parameters of cotton leaf total nitrogen were analyzed by statistical software. The correlation between biochemical parameters and wavelet coefficients and spectral values of total nitrogen in cotton leaves was analyzed by statistical software to find out the wavelet coefficients and spectral values with the highest sensitivity, and the inverse model of biochemical parameters in cotton was established by using univariate analysis, stepwise regression analysis and partial least squares method.

A. CONTINUOUS WAVELET ANALYSIS

In this study Mexican Hat wavelets are used as the mother function of the continuous wavelet transform. Each wavelet eigencoefficient contains scale and wavelength information and reflects the similarity of the function to the reflectance at a particular wavelength and scale. It has been shown that the mesoscale wavelet decomposition can truly reflect the information of chlorophyll and nitrogen content of the crop, and it can be seen from Fig. 2 that the wavelet feature scale with nitrogen correlation is mainly located in the middle and low scales, and the wavelength position is mainly located in 400-500 nm and 720 nm, and it has been analyzed before that there is a significant correlation between the nitrogen content of the leaf and the chlorophyll, and Curran concluded that there is a relationship with chlorophyll b around 460 nm and 430 nm [34], and from this experimental study it can also be seen that there is a significant correlation between nitrogen content and chlorophyll at 430-460 nm, so whether a more significant correlation between cotton leaf nitrogen content and chlorophyll b can be considered to provide an idea for future research. Secondly, due to the limitation of the measurement range of the experimental measurement instrument, the maximum wavelength is 1075 nm, but it can be seen from the figure that there is a sensitive area at the wavelength of 1075 nm, so it can be considered that there may be a more considerable sensitive area in the range after 1075 nm, and it is suggested that a spectrometer with a larger wavelength range can be used to measure in order to find more possibilities.

B. TRADITIONAL MATHEMATICAL ANALYSIS

Compared to the original spectra, derivative spectra are less affected by sun angle and crop physiology, and by using spectral slopes it is possible to convert samples with the same characteristics corresponding to different raw spectral reflectances into the same signal, reducing the redundancy of spectral data. It can be seen from Figure 3 that the derivative-treated spectra improve the correlation to nitrogen, and the stability and validity of the model are differently enhanced, and the sensitive bands with correlation to nitrogen are basically concentrated in the visible range.

C. COTTON LEAF TOTAL NITROGEN CONTENT DETECTION MODEL

From the point of view of the selected feature variables, the fit and accuracy of the model built using wavelet feature coefficients as variables is higher than that of the model built with sensitive wavelengths under the processing of traditional mathematical methods. Previous studies have also shown that the model constructed based on wavelet coefficients has better predictability, and the data decomposed by successive wavelets can increase the dimensionality to mine the useful information in the spectrum effectively. The results of B.

Rivard et al. [35] using continuous wavelet analysis with minerals showed that continuous wavelet analysis can reduce the variance in the spectral library and is applicable to vegetation studies. Meng et al. [36] selected GF-5 satellite image data and used the discrete wavelet transform to compare and analyze the spectral data of soil organic carbon at two scales of original reflectance and first-order derivative reflectance. The study showed that the discrete wavelet transform effectively eliminated the noise in the satellite hyperspectral data at low decomposition scale and significantly improved the model accuracy. In terms of the number of modeling variables, the mean R2 of the multivariate model is at 0.700 and the mean R2 of the univariate model is at 0.627, and the results indicate that the multivariate estimation capability is higher than that of the univariate model. Among the multivariate models, the R2 value of CWT-SR model was 0.8410; the R2 value of CWT-PLSR model was 0.6993, the R2 value of lg′ (1/R)-SR model was 0.6746; and the R2 value of lg′ (1/R)-PLSR model was 0.6511, from which it can be seen that the use of stepwise regression method to build models is more suitable for the prediction of cotton leaf total nitrogen The R2 value was 0.6511.

D. FUTURE RESEARCH

With the development of imaging hyperspectral technology, there is therefore the ability to build a more convenient and fast model for nitrogen monitoring through hyperspectral images by collecting hyperspectral images of sample leaves. Although continuous wavelets can further suppress their clutter interference to the raw spectra, the derivative spectra can be combined with continuous wavelet analysis due to the moment-to-moment variation of the sun's position and the differences between its crop physiological structures. The selection of sensitive bands and characteristic wavelets in this study is based on the maximum correlation coefficients, and multicollinearity can occur between adjacent wavelengths; therefore, the use of local peaks of correlation coefficients to extract sensitive bands and characteristic wavelets can be considered to reduce multicollinearity and make the reflection more comprehensive.

V. CONCLUSION

In this study, the continuous wavelet transform method and the traditional mathematical method were used to analyze the correlation with the raw hyperspectral data, to compare the contributions of both in terms of nitrogen correlation, and to evaluate the differences between the above two methods in terms of nitrogen estimation ability, and the main findings of the study are as follows:

(1) The correlations of cotton leaf total nitrogen content after the transformation of the original spectra by first-order differentiation, inverse logarithm and inverse logarithm first-order differentiation were all improved in different ways, among which the inverse logarithm first-order differentiation improved the correlation of cotton leaf total nitrogen by 0.26; the improvement of the correlation by inverse logarithm was less obvious, and the continuous wavelet analysis processing, which can effectively reduce the external factors and background conditions on the reflectance of the original spectra The continuous wavelet analysis treatment can effectively reduce the interference of external factors and background conditions on the original spectral reflectance, aiming to quickly find the effective wavelet sensitive to the biochemical parameters of cotton.

(2) The CWT cotton leaf total nitrogen estimation model established by using stepwise regression analysis has better predictive ability for the sample data than other models with the same treatment.

(3) Among the traditional spectral transformation models, the model after inverse logarithmic first-order differential transformation was higher than the other three traditional spectral transformation models in terms of prediction accuracy and model superiority.

(4) The estimation ability of CWT for cotton leaf total nitrogen content model was better than some of the traditional spectral transforms, indicating that continuous wavelet analysis is more effective in mining the hidden information in the original spectrum.

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