Remote Sensing Science
Volume 6, 2018, PP. 46-54

Nitrogen Estimation Model of Apple Leaves Based on Imaging Spectroscopy

Xin Wen[1], Xicun Zhu[1,2*], Shujing Cao , Xiaoyan Guo[1], Ruiyang Yu[1], Jingling Xiong[1], Dongsheng Gao[3]

1. College of Resources and Environment, Shandong Agricultural University, Tai'an 271018, China.
2. Key Laboratory of Agricultural Ecology and Environment, Shandong Agricultural University, Tai'an 271018, China.
3. College of Horticulture Science and Engineering, Shandong Agricultural University, National Apple Engineering and Technology Research Center, Tai'an 271018, China.

Abstract

Imaging spectrometer was used to measure the spectral data of apple leaves. The spectral reflectance of apple leaves was extracted. The nitrogen content of apple leaves was correlated with the spectral reflectance after SG smoothing first-order differential treatment. The sensitive wavelengths were selected and nitrogen content prediction models were founded. The results showed that the spectral of apple leaves with different concentration gradients were obvious. The higher nitrogen content was, the lower spectral reflectance was. Established estimation models by using the selected SG smooth first-order differential spectral sensitive wavelengths SG-FDR_{403}, SG-FDR_{469}, SG-FDR_{525}, SG-FDR_{566}, SG-FDR_{650}, SG-FDR_{696}, SG-FDR_{781}, SG-FDR_{851}, SG-FDR_{933} .The determined coefficient (R^2) of the partial least squares model was 0.5202. The root mean square error (RMSE) of that was 2.19 and the relative error (RE) of that was 5.89%. The R^2 of the support vector machine (SVM) model was 0.724. The RMSE of that was 1.94, and the RE of that was 5.13%. It is indicated that the SVM model can estimate the nitrogen content of apple leaves effectively.

Keywords: Apple Leaves; Nitrogen; Hyperspectral Imaging; Support Vector Machine

1. INTRODUCTION

The traditional method for detecting nitrogen content in vegetation leaves is to collect samples in the field and use chemical methods to measure nitrogen content in the laboratory. Although this method has high measurement accuracy, it requires a lot of manpower, material resources and financial resources in the measurement process. It takes a long time. Hyperspectral technology with the rapid, real-time and non-destructive features have become an important method for detecting vegetation nitrogen content and monitoring vegetation growth[1-2] in recent years. Imaging spectroscopy combines imaging technology with hyperspectral technology to take advantage of both hyperspectral and imaging. A large number of scholars all over the world have used hyperspectral techniques to obtain vegetation nitrogen information[3-6]. Thomas *et al.*[7] found that the nitrogen content of sweet pepper leaves is related to the spectral reflectance of leaves in the 550-675 nm spectrum.The error between the measured and predicted values of leaf nitrogen is small, indicating that the use of hyperspectral technology may be fast. Elfatih M Abdel-Rahman *et al.*[8] proposed a random forest regression algorithm using hyperspectral data to predict the nitrogen content of sugarcane leaves; Li Jinmeng *et al.*[9] established the prediction model of nitrogen content in leaves of citrus plants under different preprocessing conditions .by using imaging spectroscopy It was proved that the back propagation artificial neural network model is more suitable for the prediction of nitrogen content in citrus leaves; Wang Renhong[10] established an empirical model of different nitrogen levels and winter wheat nitrogen nutrition. The index was conducted to show the parameter inversion of leaf nitrogen content and canopy nitrogen density. The results showed that NNI has certain diagnosis of nitrogen nutrition status. .The advantage of qualitative and quantitative diagnosis of nitrogen nutrition status by hyperspectral inversion of nitrogen is feasible; Yu Keqiang *et al.*[11-12] set the model by the hyperspectral imaging data, SPAD and total nitrogen content of pepper leaves. The PLSR model with characteristic bands was established, and the distribution maps of SPAD and total nitrogen content of pepper leaves were depicted. Wang Lifeng[13-14] researched by the corn different nitrogen concentration treatments. The spectral data was transformed and constructed a variety of spectral parameters. Zhou Lili *et al.*[15] applied hyperspectral imaging technology to estimate the nitrogen content of corn leaves.The research achieved the good results.

Hyperspectral imaging technology is becoming more mature in terms of vegetation nutrient inversion, while the research applied to fruit trees is less. Nitrogen of apple leaves is an important element for its growth. It affected the growth and yield of apple trees, causing the changes in its hyperspectral characteristics[16-20]. In this study, hyperspectral imaging technology was used to select the sensitive bands of nitrogen content, and the nitrogen estimation model was established to find an efficient and convenient method for detecting nitrogen content for apple leaves.

2 .Experimental Materials and Methods

2.1 Sample Collection

The sample was collected in the Apple Park of Qixia City, Yantai City, Shandong Province. According to the land use planning map and orchard distribution map of Qixia City, the collection points were collected. In May 2017, the apple leaves of Qixia Apple Orchard were collected and 157 apple trees were selected. In order to ensure the representativeness of the experimental results, the selected fruit trees were selected. Covering different tree ages and different tree potentials, two healthy leaves with sufficient maturity, losslessness and no pests and diseases were collected as a sample on the vegetative shoots in the middle of each apple tree. After numbering, quickly load it into the foam box containing the ice pack.

2.2 Data Measurement

1) DeterMination of Nitrogen Content

The nitrogen content of apple leaves was determined by Kjeldahl method. A total of 157 leaf sample data were collected in this study. 118 samples (75%) were randomly selected as the modeling set, and the remaining 39 samples (25%) were used as test sets.

2) Hyperspectral Data Measurement

Apple leaf hyperspectral imaging data was measured using a US SOC710VP portable spectral imager. Its instrument spectral range: 400 ~ 1000nm, spectral resolution 4.68nm, 128 bands. According to the hyperspectral imaging data acquisition system, assemble the instruments, place the standard gray board on the horizontal surface, fix the imaging spectrometer with a tripod, make the instrument lens perpendicular to the center of the gray board, and place the sample to be measured in the center of the gray board to ensure the halogen lamp. For the sole source, the rotating imaging spectrometer lens adjusts the focus to a clear sample and acquires a hyperspectral image.

The acquired imaging hyperspectral image is an untransformed DN value. Converting the DN value in the image to reflectance requires wavelength calibration, radiometric calibration, and conversion reflectance according to the reference version. After the reflectance is normalized, the imaging hyperspectral data of the reflectance is obtained.

2.3 Spectral Data Extraction

The reflectance was extracted from the normalized imaging hyperspectral image using the software of ENVI 5.1. The imaging hyperspectral data normalized by the reflectance is imported into the ENVI 5.1 software to select the region of interest. Among them, when selecting the region of interest, care should be taken to avoid the position where the surface reflectance of the blade is high or low, and the shadows and highlights in the image are excluded, and the main vein of the blade is avoided. Display the image RGB image in the software, observe the leaf reflectivity by clicking on different areas of the blade in the image. According to the reflectivity and the depth of the leaf color in the image, select two regions at different positions of each blade as the ROI. A total of 4 regions were selected as the region of interest for each sample, and the hyperspectral average of all points in the region of interest was extracted as the hyperspectral data of the sample[21-22].

2.4 Spectral Pretreatment of Apple Leaves

When obtaining sample spectral data, due to the influence of environment, instrument, human operation and sample itself, it is easy to cause a large amount of noise and interference information in the spectral curve, and the acquired spectrum needs to be preprocessed to improve the signal-to-noise ratio of the spectral data. However, spectral noise is still inevitable, and the noise spectrum inevitably affects the analysis of spectral data. Therefore, the spectral information is preprocessed, and the spectral noise is removed from the spectral curve as much as possible to improve the validity of the spectral information and accurately locate the effective spectral band.

1) S-G Smoothness

Smoothing filtering is one of the commonly used preprocessing methods in spectral analysis. Smoothing with the Savitzky-Golay method can improve the smoothness of the spectrum and reduce the noise interference. The purpose of each measurement with the smoothing coefficient is to minimize the effect of smoothing on useful information. It can be based on the principle of least squares.

2) First Order Linear Differential

Derivative transformation is an effective spectral preprocessing method. Using derivative transform to process hyperspectral data, it is possible to effectively separate the absorption peaks from the overlapping absorption spectra and better determine the position of sensitive wavelengths of apple leaves. In addition, it can be used to correct the spectral baseline, eliminate the influence of other background interference on the sample spectrum, and improve the spectral resolution.

The first-order differential analysis calculation formula is as follows：

$$\mathrm{FDR}i = \frac{\mathrm{R}_{\mathrm{i}+1} - \mathrm{R}_{\mathrm{i}-1}}{(\lambda_{i+1} - \lambda_{i-1}) + (\lambda_{i+1} - \lambda_{i-1})} = \frac{\mathrm{R}_{\mathrm{i}+1} - \mathrm{R}_{\mathrm{i}-1}}{2\Delta\lambda}$$

FD, first derivative of reflectance;
R, Leaf spectral reflectance;
I, Reflectance value corresponding to wavelength position;
λ, Reflectance corresponding to wavelength.

2.5 Model Establishment and Inspection Method

1) Estimation Models

Two models suitable for leaf nutrient inversion were selected which based on the previous studies, namely support vector machine (SVM) and partial least squares (PLS).

SVM is a learning machine first proposed by Corinna Cortes and Vapnik in 1995. It shows many unique advantages in solving small sample, nonlinear and high-dimensional pattern recognition. It can be applied to other machine learning problems. The SVM is based on the VC dimension theory and structural risk minimization principle of statistical learning theory. According to the limited sample information, the best concession was founded between the complexity of the model (learning accuracy for specific training samples) and the learning ability (the ability to identify any sample without error) to obtain the best ability of promotion.

PLS is an important method of multivariate statistical analysis, which was first proposed by Wood and Abano in 1983. In the past ten years, it has developed rapidly in theory, method and application. It is the regression modeling method for multi-dependent variables to multiple independent variables, which can realize the comprehensive application of various data analysis methods.

2) Model Checking Method

In the modeling and verification process, the model needs to be evaluated and optimized, and some statistical parameters are usually used, This study selected the three most commonly used model test parameters, R^2, *RMSE* and *RE was* calculated as follows:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(yi - \hat{y}\mathrm{i})^2}{\sum_{i=1}^{n}(yi - \overline{yi})^2}$$

$$RMSE = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(yi - \hat{y}i)^2}$$

$$RE = \frac{1}{n}\sum_{i=1}^{n}\frac{|yi - \hat{y}i|}{yi} \times 100\%$$

R^2 indicates the degree of closeness between the measured value and the estimated value. RMSE and RE indicate the degree of dispersion between the measured value and the predicted value. The larger the R^2 is, and the smaller the RMSE and RE are, the more accurate the estimation is.

3. Results and Analysis

3.1 Spectral Characteristics of Apple Leaves with Different Nitrogen Contents

According to the order of nitrogen concentration from low to high, the data were divided into three groups, which were 52, 52, and 51. The spectral reflectance of each group was averaged, and the nitrogen content of apple leaves at three concentration levels was obtained. The hyperspectral data were ordered by 27 $g.kg^{-1}$, 31 $g.kg^{-1}$ and 34 $g.kg^{-1}$.Figure 1 was obtained.

It can be seen from Fig. 1 that the spectral curves of apple leaves with different nitrogen contents have the same trend, but the spectral reflectance responses of apple leaves are different in different bands. In the blue band and the red band, from which the leaves absorb the light for photosynthesis, the red-blue region has a low reflectance. The difference in the spectral curve of the apple leaves with different nitrogen contents is small. The difference is the most obvious in reflectance of apple leaves in the green band and in the 780 nm to 1000 nm band. At the green peak, the spectral curve of 27 $g.kg^{-1}$ has the highest reflectance. The spectral curve of 31 $g.kg^{-1}$ is the second, and the spectral curve of 34$g.kg^{-1}$ has the lowest reflectance. They can be used as basis for qualitatively determining the nitrogen content of apple leaves. At the green peak (550 nm), the higher the spectral reflectance, the lower the nitrogen content of apple leaves.

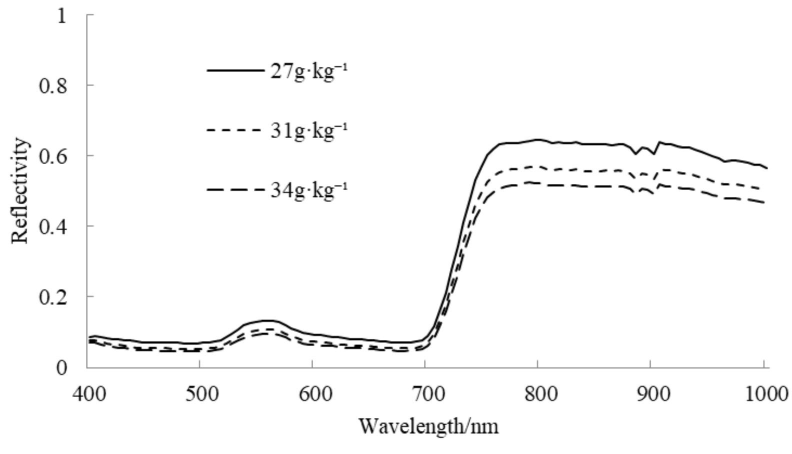

Fig.1 Spectral curves of different nitrogen content in apple leaves

3.2 Relationship between Nitrogen Content in Apple Tree Leaves and Original Spectral Reflectance

Figure 2 is a plot of the original hyperspectral reflectance of apple tree leaves and its leaf nitrogen content. The results showed that the nitrogen content of apple leaves was negatively correlated with its corresponding hyperspectral range from 400 nm to 100 nm, and the absolute value of correlation between green light region (500nm-570nm) and red edge region (700nm-750nm) was relatively high. It indicates that there is a large correlation between the bands of these two regions and the nitrogen content of apple leaves, reaching maximum values at 550 nm and 723 nm, which are 0.685 and 0.682, respectively.

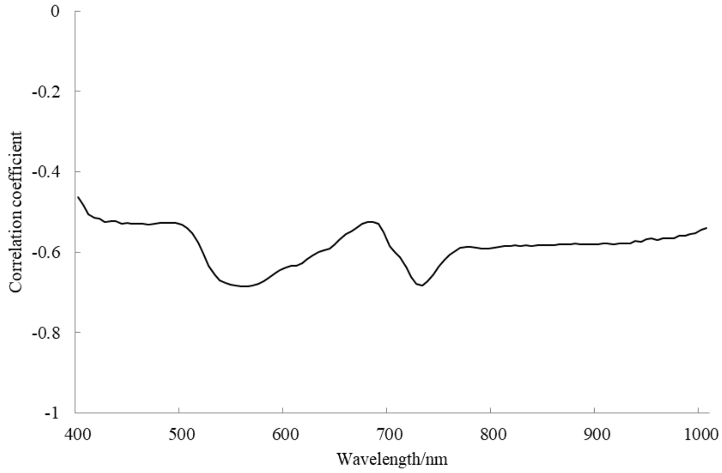

Fig.2 Correlation between original spectral reflectance of apple leaves and nitrogen

3.3 Relationship between Nitrogen Content in Apple Leaves and Spectral Reflectance of Pretreatment

Spectral information acquired by imaging hyperspectral technology contains a large amount of redundant information, which affects the qualitative and quantitative analysis of spectral data. To eliminate noise and interference information in spectral data, the acquired spectral information needs to be preprocessed. The Savitzky-Golay method was used to perform smoothing and first-order differential processing on the original spectral data using the software of MATLAB.

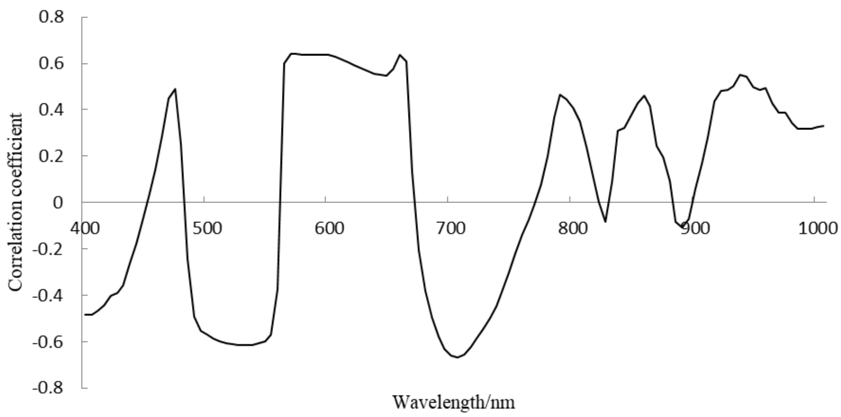

Fig. 3 Correlation between spectral reflectance and nitrogen content after first-order differential treatment of apple leaf SG smoothing

Figure 3 is a graph showing the correlation between the high-spectral reflectance of apple leaves and nitrogen content after SG smoothing and first-order differential treatment. The results show that in the visible light range, the spectral reflectance SG smoothing first-order differential of apple leaves is negatively correlated with nitrogen content in the range of 400nm-450nm, 480nm-556nm and 665nm-760nm, 450nm-480nm, 556nm- In the two wavelength ranges of 665nm, the first-order differential of SG smoothing of the leaf reflectance of apple leaves was positively correlated with the nitrogen content. In the range of 760nm-1000nm, the first-order differential of the spectral reflectance of apple leaves was positively correlated with the nitrogen content. There is a negative correlation at the two wavelengths of 820 nm and 900 nm. The correlation between the first derivative spectral spectrum and the nitrogen content of the apple leaf SG is compared with the original correlation. The band with a large correlation coefficient is similar to the original spectrum, but its peak is more prominent, mainly due to the original spectrum. SG smooth derivation can reduce background noise and improve the extraction efficiency of target information, thus enhancing the correlation between spectrum and nitrogen.

The wavelength at the inflection point of the curve with higher correlation is selected as the sensitive wavelength. As shown in Table 1, a total of 9 wavelengths with a large correlation coefficient with the nitrogen content of apple leaves were selected as sensitive wavelengths, they are SG-FDR_{403}, SG-FDR_{469}, SG-FDR_{525}, SG-FDR_{566}, SG-FDR_{650}, SG-FDR_{696}, SG-FDR_{781}, SG-FDR_{851}, SG-FDR_{933}.

Table 1 Correction Coefficients between SG Smoothing First Derivative of Spectral Sensitive Reflectivity of Apple Leaves and Nitrogen Content of Apple Leaves

SG smoothing- first derivative of remarkable wavelengths	**Correlation coefficients**	**SG smoothing- first derivative of remarkable wavelengths**	**Correlation coefficients**
SG-FDR_{403}	-0.48	SG-FDR_{696}	-0.67
SG-FDR_{469}	-0.49	SG-FDR_{781}	0.47
SG-FDR_{525}	-0.61	SG-FDR_{851}	0.46
SG-FDR_{566}	0.55	SG-FDR_{933}	0.55
SG-FDR_{650}	0.64		

3.4 Nitrogen Prediction Model of Apple Leaves Based on Partial Least Squares

The PLS model of nitrogen content was established by using SG-FDR_{403}, SG-FDR_{469}, SG-FDR_{525}, SG-FDR_{566}, SG-FDR_{650}, SG-FDR_{696}, SG-FDR_{781}, SG-FDR_{851} and SG-FDR_{933} as independent variables. The results of calibration set were the R^2 of 0.5389, the RMSE of 2.20, and the RE of 5.97%. The results of verification set were shown in Fig. 4. The R^2 of measured and predicted values was 0.5202. The RMSE and RE of those were 2.19 and 5.89%.

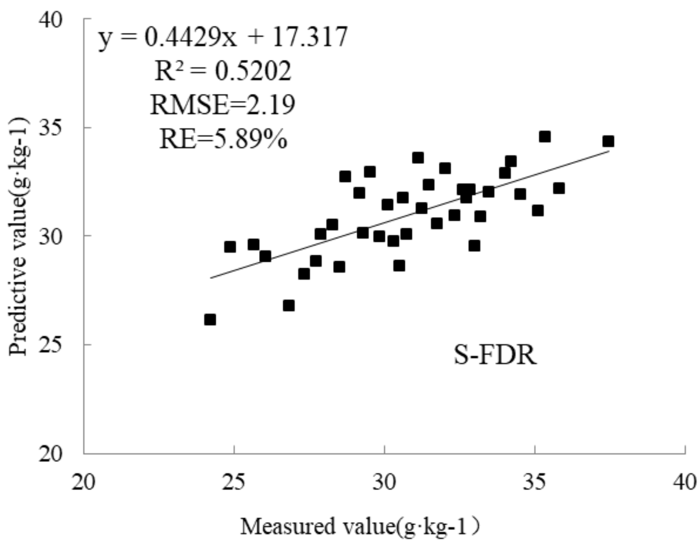

Fig. 4 SG smoothing first-order differential spectral partial least squares model test fitting

3.5 Nitrogen Prediction Model of Apple Leaf Based on Support Vector Machine Regression Model

Using the selected sensitive wavelengths SG-FDR$_{403}$, SG-FDR$_{469}$, SG-FDR$_{525}$, SG-FDR$_{566}$, SG-FDR$_{650}$, SG-FDR$_{696}$, SG-FDR$_{781}$, SG-FDR$_{851}$ and SG-FDR$_{933}$ as independent variables and the nitrogen content of apple leaves as dependent variables, a support vector machine regression model was established. The results of calibration set were the R^2 of 0.8077, the RMSE of 1.44, and the RE of 3.30%. The results of verification set were shown in Fig. 4. The R^2 of measured and predicted values was 0.724. The RMSE and RE of those were 1.94 and 5.13%. It can be seen that the fitting effect between the measured value and the predicted value is better, which indicates that the SVM regression model has better estimation ability and can accurately estimate the nitrogen content of apple leaves[23].

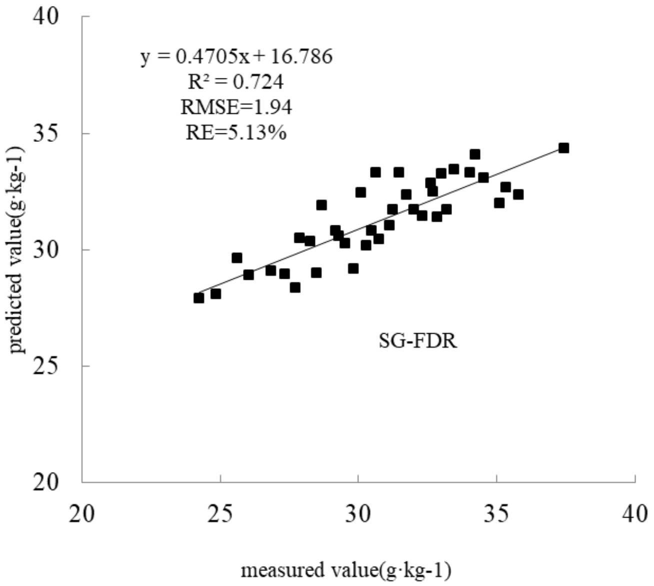

Fig. 5 Support vector machine regression model model test fitting

3.6 Model Comparison

The spectral characteristics of apple leaves with different concentration gradients of nitrogen content showed the characteristics that the higher the nitrogen content, the lower the light reflectance. The relationship between the original spectral reflectance and the reflectance of SG smoothing first-order differential processing and apple nitrogen was analyzed, and the sensitive wavelengths SG-FDR$_{403}$, SG-FDR$_{469}$, SG-FDR$_{525}$, SG-FDR$_{566}$, SG-FDR$_{650}$, SG-FDR$_{696}$, SG-FDR$_{781}$, SG-FDR$_{851}$, SG-FDR$_{933}$. Using the partial least squares method and the SVM regression model established by the nine sensitive wavelengths, the model training results are compared with the R^2 of the model detection result, the RMSE, and the RE. The model training result of R^2 was 0.5389, the RMSE was 2.20, the RE was 5.97%; the measured value and predicted value R^2 was 0.5202, RMSE was 2.19, and the RE was 5.89%. The R^2 of the SVM was 0.8077, the RMSE was 1.44, the RE was 3.30%; the measured value and predicted value R_2 was 0.724, the RMSE is 1.94, and the RE is 5.13%. It can be seen that the measured value of the SV has a better fitting effect with the predicted value, and the reliability and accuracy of the model are higher.

4. CONCLUSION

The PLS model and the SVM regression model were established. Compared with the SVM regression model, the R^2 is 0.724, the RMSE is 1.94, and the RE is 5.13%. The model accuracy is far. Higher than the partial least squares regression model, it is indicated that the nitrogen content estimation model of apple leaves established by the SVM regression model can effectively estimate the nitrogen content of apple leaves.

ACKNOWLEDGMENTS

This paper was supported by the National Natural Science Foundation of China (41671346), Funds of Shandong “Double Tops” Program（SYL2017XTTD02）, Shandong major scientific and technological innovation project: Research demonstration and extension of orchard irrigation and fertilization in accurate management (2018CXGC0209).

REFERENCES

[1] Zhang Xiaolei, Liu Fei, Nie Pengcheng, He Yong, Bao Yidan. Rapid determination of nitrogen content and distribution in rape leaves by hyperspectral imaging [J]. Spectroscopy and spectral analysis, 2014, 34 (09): 2513-2518.

[2] Tian Yongchao, Zhu Yan, Yao Xia, Liu Xiaojun, Cao Satellite. Nondestructive monitoring of crop nitrogen nutrition based on spectral information [J]. Journal of Ecology, 2007 (09): 1454-1463.

[3] Huang Shuangping, Hong Tiansheng, Yue Xuejun, Wu Weibin, Cai Kun, Xu Xing. Multivariate regression analysis of nitrogen content in Citrus Leaves Based on hyperspectral data [J].Journal of Agricultural Engineering, 2013, 29 (05): 132-138.

[4] Yi Peng, Anatoly A. Gitelson. Remote estimation of gross primary productivity in soybean and maize based on total crop chlorophyll content [J]. Remote Sensing of Environment, 2011, 117.

[5] Moghaddam P A, Derafshi M H, Shirzad V. Estimation of single leaf chlorophyll content in sugar beet using machine vision [J]. Turkish Journal of Agriculture & Forestry，2011, 35 (6):563-568. Steddom M W K，Bredehoeft M，Khan M，Rush M C. Compariaon of visual and multispectral radiometric disease evaluation of Cercospora leaf spot of sugar beet [J]. Plant Disease, 2005. 89 (2): 1123-1130.

[6] Liao Qinhong, Wang Jihua, Yang Guijun, et al. Comparison of spectral indices and wavelet transform for estimating chlorophyll content of maize from hyperspectral reflectance [J]. Journal of Applied Remote Sensing, 2013, 7(1):1-11

[7] Thomas J R, Oerther G F. Estimating nitrogen content of sweet pep-per leaves by reflectance measurements [J]. Agronomy Journal, 1971, 64(1):11-13.

[8] Elfatih M Abdel-Rahman, Fethi B Ahmed, Fethi B Ahmed, Riyad Ismail. International Journal of Remote Sensing, 2013, 34(2):712

[9] Li Jinmeng. Rapid determination of nitrogen content in Citrus Leaves Based on hyperspectral imaging [D]. Zhejiang University, 2014.

[10] Wang Renhong, Song Xiaoyu, Li Zhenhai, Yang Guijun, Guo Wenshan, Tan Changwei, Chen Liping. Estimation of nitrogen nutrition index of Winter Wheat Based on hyperspectral data [J]. Journal of Agricultural Engineering, 2014, 30 (19): 191-198.

[11] Yu Keqiang, Zhao Yanru, Li Xiaoli, Ding Xibin, Chuang Zai Chun, He Yong. Visualization of Nitrogen Distribution in Pepper Leaves at Different Positions by Hyperspectral Imaging [J]. Spectroscopy and Spectral Analysis, 2015, 35 (03): 746-750.

[12] Zhao Yanru, Yu Keqiang, Li Xiaoli et al. [J] Visualization of chlorophyll distribution in pumpkin leaves based on Hyperspectral imaging. Spectroscopy and spectral analysis, 2014, 34 (5): 1378-1382.

[13] Wang Lifeng, Zhang Changli, Zhao Yue, Song Yuzhu, Wang Runtao, Jiangsu Zhongbin, Wang Shuwen. Detection model of nitrogen content in maize leaves by hyperspectral imaging [J]. Agricultural mechanization, 2017, 39 (11): 140-147.

[14] Wang Shuwen, Zhao Yue, Wang Lifeng, Wang Runtao, Song Yuzhu, Zhang Changli, Central Jiangsu. Prediction of nitrogen content in rice leaves in cold regions based on hyperspectral data [J]. Journal of Agricultural Engineering, 2016, 32 (20): 187-194.

[15] Zhou Lili, Feng Hanyu, Yan Zhongmin, Liu Ke, Zhou Shun. Hyperspectral estimation of nitrogen content in maize leaves and its varietal differences [J].Journal of Agricultural Engineering, 2010, 26 (08): 195-199.

[16] Zhu Xicun, Zhao Gengxing, Wang Ling, Dong Fang, Lei Tong, and Zhenbing. Prediction model of nitrogen content in apple blossoms based on hyperspectral data [J]. Spectroscopy and spectral analysis, 2010, 30 (02): 416-420.

[17] Liang Shuang, Zhao Gengxing, Zhu Xicun. Hyperspectral estimation model of chlorophyll content in apple leaves [J]. Spectroscopy and spectral analysis, 2012, 32 (05): 1367-1370.

[18] Fang Xianyi, Zhu Xicun, Wang Ling, Zhao Gengxing. Monitoring of chlorophyll content in Apple canopy during full-fruit period based on Hyperspectral data [J]. China Agricultural Sciences, 2013, 46 (16): 3504-3513.

[19] Han Zhaoying, Zhu Xicun, Fang Xianyi, Wang Zhuoyuan, Wang Ling, Zhao Gengxing, Jiang Yuanmao. LAI Hyperspectral Estimation of Apple Crown Based on SVM and RF [J]. Spectroscopy and spectral analysis, 2016, 36 (03): 800-805.

[20] Cheng Lizhen, Zhu Xicun, Gao Lu, Wang Ling, Zhao Gengxing. Hyperspectral estimation of phosphorus content in Apple Leaves Based on random forest model [J]. Acta Fruit Tree, 2016, 33 (10): 1219-1229.

[21] Sun Jun, Jin Xiameng, Mao Hanping, Wu Xiaohong, Zhang Xiaodong, Gao Hongyan. Prediction model of nitrogen content in lettuce leaves based on hyperspectral images [J]. Analytical Chemistry, 2014, 42 (05): 672-677.
[22] Liu Yande, Jiang Xiaogang, Zhou Yanhua, Liu Deli. Quantitative analysis of chlorophyll, water and nitrogen in navel orange leaves based on hyperspectral imaging technology [J]. China Agricultural Mechanochemistry Journal, 2016, 37 (03): 218-224.
[23] Liang Liang, Yang Minhua, Zhang Lianpeng, Lin Hui, Zhou Xingdong. Hyperspectral inversion of chlorophyll content in wheat canopy based on SVR algorithm[J]. Journal of Agricultural Engineering, 2012, 28(20): 162-171+294.

Authors

Xin Wen, she is working on his Master degree in Agricultural Information major at Shandong Agricultural University. Her research interest is agricultural information.

Xicun Zhu, he is an associate professor in College of Resources and Environment Shandong Agricultural University. His research interests include the applications of agricultural remote sensing and information technology.

Shujing Cao, she is working on her Master degree in Land Resource Management major at Shandong Agricultural University. Her research interest is agricultural remote sensing.

Xiaoyan Guo, she is working on her Master degree in Land Resource Management major at Shandong Agricultural University. Her research interest is hyperspectral remote sensing.

Ruiyang Yu, he is working on his Master degree in Cartography and Geographic Information Engineering major at Shandong Agricultural University. His research interest is hyperspectral remote sensing.

Jingling Xiong, she is working on her Master degree in Land Resource Management major at Shandong Agricultural University. Her research interest is hyperspectral remote sensing.