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Estimating Nitrogen Contents Of Apple Leaves Based On Hyperspectral Parameter Models At Different Phenophases

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Abstract

The objective of the paper is to explore the best phenophase for estimating the nitrogen contents of apple leaves, to establish the best estimation model of the hyperspectral data at different phenophases. It is to improve the apple trees' precise fertilization and production management. The experiments were done in 20 orchards in the field, measured hyperspectral data and nitrogen contents of apple leaves at three phenophases in two years, which were shoot growth phenophase, spring shoots pause growth phenophase, autumn shoots pause growth phenophase. The study analyzed the nitrogen contents of apple leaves with its original spectral and first derivative, screened sensitive wavelengths of each phenophase. The hyperspectral parameters were built with the sensitive wavelengths. Multiple stepwise regressions, partial least squares and BP neural network model were adopted in the study. The results showed that 551 nm, 716 nm, 530 nm, 703 nm; 543 nm, 705 nm, 699 nm, 756 nm and 545 nm, 702 nm, 695 nm, 746 nm were sensitive wavelengths of three phenophases. $R_{551}+R_{716}$, $R_{551}*R_{716}$, $FDR_{530}+FDR_{703}$, $FDR_{530}*FDR_{703}$; $R_{543}+R_{705}$, $R_{543}*R_{705}$, $FDR_{699}+FDR_{756}$, $FDR_{699}*FDR_{756}$ and $R_{545}+R_{702}$, $R_{545}*R_{702}$, $FDR_{695}+FDR_{746}$, $FDR_{695}*FDR_{746}$ were the best hyperspectral parameters of each phenophase. Of all the estimation models, the estimated effect of shoot growth phenophase was better than other two phenophases, so shoot growth phenophase was the best phenophase to estimate the nitrogen contents of apple leaves based on hyperspectral models. In the three models, the 4-3-1 BP neural network model of shoot growth phenophase was the best estimation model. The R^2 of estimated value and measured value was 0.6307, RE% was 23.37, RMSE was 0.6274.

Key words: Different Phenophases; Apple Leaves; Nitrogen Contents; Hyperspectral Parameters;

N (Nitrogen, N) is one of the important elements needed for plant growth. The absorption of N from the soil is an important indicator reflects the growth conditions of them (Shangguan & Li, 2004). When apple trees lack of N, the chlorophyll content of their leaves will decrease and they will have fewer fruits. When N is overdoes, the shoots will grow strong and the leaves will grow large and thin and have a poor accumulation of nutrition. It not only delayed the fruit ripening, but also causes environmental pollution. Applying the right amount of N fertilizer can help apple trees grow healthy. Therefore, how to monitor the N content of the apple trees in real-time, rapidly and accurately is a key issue worthy of study.

The traditional method to measure N is accurate, but it wastes time and energy. With the development of hyperspectral remote sensing, it has become possible to estimate the N content of apple leaves using the hyperspectral technology quickly and accurately. At present, the use of hyperspectral technology in the spectral analysis and estimation of the N content of leaves in wheat (Hansen & Schjoerring, 2003; Xue et al., 2004; Dai et al., 2007; Yao et al., 2009), corn (Cho M A & Skidmore A K, 2006; Liu et al., 2012), cotton (Tarpley et al., 2000; Wu et al., 2007), rice (Shibayama & Akiyama, 1993; Liu et al., 2006; Tian et al., 2010) and other crops have been widely studied. In fruit research, P. Menesatti et al. (2010) and Yi Shelley et al. (2010) had used oranges as experimental subjects, and they established a model for estimating N content of leaves by using partial least squares and hyperspectral data. Zhu Xicun et al. (2010) and Li Bingzhi et al. (2010) had done quantitative inversion of N content in apple blossoms and leaves with hyperspectral data respectively. Huang Shuangping et al. (2013) had studied the citrus leaves at different growth funnies' and predicted the N content of citrus leaves using support vector regression method successfully. Li Ping et al. (2013) had studied the Korla fragrant pear trees and found that the estimation model of first-order ordinary differential spectral established by the spectral reflectance data at 703 nm had a better effect. The estimation of N content in fruit trees in previous are mostly only one phenophase, and the study of several phenophases is rarely reported. Shoot growth phenophase, spring shoots pause growth phenophase, autumn shoots pause growth phenophase are three important phenophases of apple trees. Shoot growth phenophase is the center stage during the distribution of nutrients. Spring shoots pause growth phenophase and autumn shoots pause growth phenophase is the appropriate time to fertilize.

In this study, Fuji apple trees about 15 years in the Yantai Qixia City, Shandong Province are chosen as research subjects. Hyperspectral reflectance and N content in leaves of shoot growth phenophase, spring shoots pause growth phenophase, autumn shoots pause growth phenophase are measured respectively. The correlation between the original spectrum and its first derivative spectral data and N content of apple leaves is analyzed. Sensitive wavelengths are chosen and build hyperspectral parameters are built and hyperspectral parameter estimation models of N content in apple leaves of different phenophases are established. After inspection of the estimation model, the best phenophase and optimal estimation model to estimate N content in apple leaves are determined. The study is done to provide technical support for information management and precision fertilization to apple trees.

1 Material and Methods

1.1 Study Sites

The study is carried out in station of Qi Xia, Shandong Province in China. It is situated at 37°05′~37°32′N and 120°33′~121°15′E. It is located in the center of Shandong Peninsula and mainly has mountainous and hilly. Its altitude is about 178 m. There are a temperate monsoon climate and the average temperature is 11.3℃. The average annual precipitation is 754 millimeters. The frost-free period lists about 207 days and the illumination time up to 2690 hours. The temperature difference is large in the autumn and its soil is brown. The natural environment is very suitable for growing apple trees.

1.2 Collecting samples

Samples were collected in May (shoot growth phenophase), June (spring shoots pause growth phenophase), September (autumn shoots pause growth phenophase) 2013 and 2014. Within 20 orchards in Qixia are selected randomly. Fuji apple trees growing well and about 15 years old are selected (avoid trees near the highway in an orchard), and took two leaves which are the same size and health of apple tree branches around. Eight leaves of one apple tree are collected. Three apple trees of each orchard are selected and sixty trees are selected by all. The leaves are put into ziplock bags after sealing. The bags are put into the foam box after numbering, and then back to the laboratory to measure hyperspectral data and the N content in the leaves.

1.3 Leaf spectral reflectance measurement

The spectral reflectance is measured with the help of the FieldSpec 3 portable field spectrometer. Its spectrometer band ranges from 350 nm to 2500 nm. The sampling intervals are 1.4 nm (350-1000 nm) or 2 nm (1 000-2 500 nm). A white panel is used to obtain a reference signal in the prioritization of measurement, and correct the spectrometer with the whiteboard every 20 minutes. The leaves are cleaned with a clean paper. Leaf spectral reflectance is measured by the Unit 1636 Plant Probe at the middle part of the eight leaves picked from 60 apple trees separately (pay attention to avoid the veins). Each measurement of the spectral readings takes ten times. The mean of the eight parts is taken as the spectral reflectance of each tree.

1.4 The determination of the N content

Put the leaves into the oven at 105 ℃ about 15 minutes after measuring the spectrum, and then drying to constant weight at 75 ℃. Put the apple leaves into powder after drying and digestion, and then measure the N content using by the Kjeldahl determination. The instrument equipment is N KDY-9820.

1.5 Data Analysis

The correlation analysis is done by analyzing the N content and leaf original spectral reflectance and first derivative value through Excel of three phenophases. According to the maximum principle for the correlation coefficient, the study determines sensitive wavelengths which are sensitive to the N content of the apple tree leaves. Then the hyperspectral parameters were built with the sensitive wavelengths.

The 60 samples collected in 2013 are chosen to establish the estimation model and the 60 samples collected in 2014 are used to test the model. The performance of the model is evaluated by comparing the differences in the coefficient of determination (R^2), root mean square error (RMSE) and relative error (RE%). By comparison and screening, and ultimately determine the best phenophase to estimate N content of apple leaves and the best estimation model. The data analysis of 2013 and 2014 is shown in Table 1.

Table 1 The Statistical Analysis of Research Data

Growth phenophase	Sample Classification	Sample Number	Maximum	Minimum	Average	Standard Deviation
Shoot growth phenophase	Modeling samples	60	3.343	2.553	2.988	0.174
	Testing samples	60	2.990	2.244	2.684	0.1515
Spring shoots pause growth phenophase	Modeling samples	60	3.752	2.444	2.977	0.323
	Testing samples	60	3.247	1.676	2.575	0.298
Autumn shoots pause growth phenophase	Modeling samples	60	2.942	2.155	2.612	0.169
	Testing samples	60	2.848	2.050	2.472	0.163

2 RESULTS AND ANALYSIS

2.1 Hyperspectral curve analysis of the different phenophases of apple tree leaves

As shown in Figure 1, the trend of spectral curves of the different phenophases of apple leaves is consistent. But in the visible range, the differences of reflectance between different phenophases are significant. It may be due to different nutrient contents of different phenophases. Therefore the use of hyperspectral parameter to estimate apple leaf N content of apple leaves is feasible.

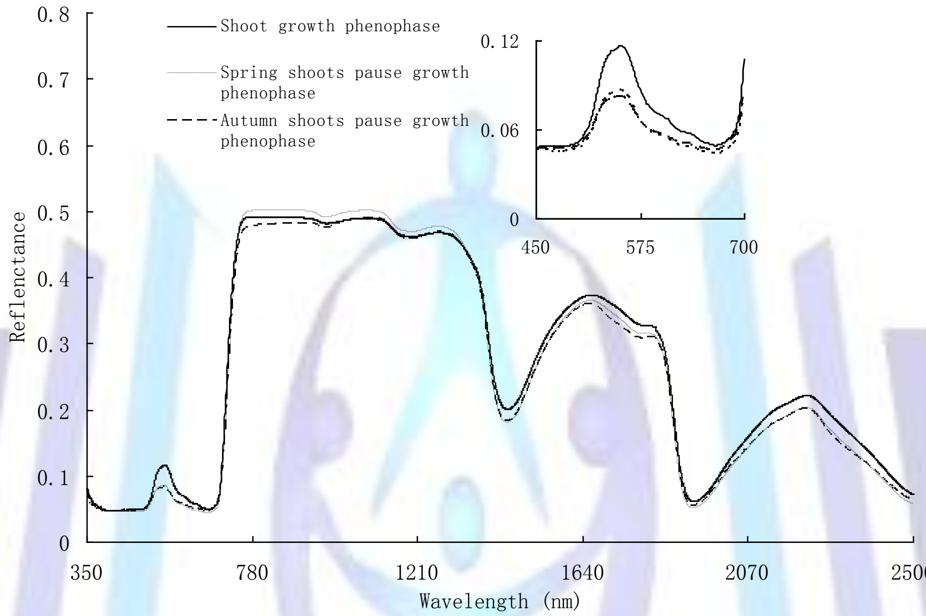
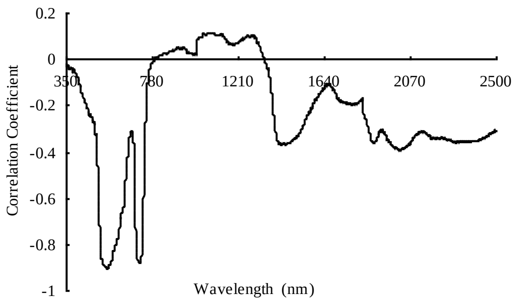


Fig. 1 Hyperspectral curves of apple leaves at different phenophases

2.2 Correlation analysis between the hyperspectral reflectance and the N content of the apple tree leaves

As shown in Figure 2, the correlation coefficient between the hyperspectral reflectance and the N content reaches maximum at 551 nm and 716 nm, which are 0.9036 and 0.8816 respectively. The correlation coefficient between the first derivative reflectance and the N content reaches maximum at FDR_{530}, FDR_{566}, FDR_{703} and FDR_{741}. Among them, FDR_{530} and FDR_{703} is bigger which are 0.8412 and 0.8277.Thus $R_{554,}$ R_{713}, FDR_{530} and FDR_{703} can be taken at sensitive wavelengths for estimating the N content.

Similarly, the sensitive wavelengths of spring shoots pause growth phenophase and autumn shoots pause growth phenophase are selected. The sensitive wavelengths of three phenophases can be seen in Table 2.



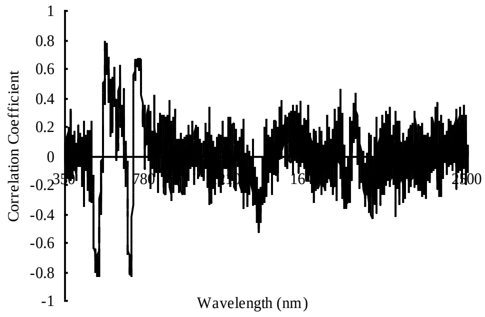


Fig. 2 Correlation of the original spectral reflectance and first derivative spectral reflectance with nitrogen contents of apple leaves at shoot growth phenophase

Table 2 The sensitive wavelength selected at different phenophases

Shoot growth phenophase	Spring shoots pause growth phenophase	Autumn shoots pause growth phenophase
R_{551}	R_{543}	R_{545}
R_{716}	R_{705}	R_{702}
FDR_{530}	FDR_{699}	FDR_{695}
FDR_{703}	FDR_{756}	FDR_{746}

2.3 Building hyperspectral parameters

In order to reduce the contingency of single sensitive wavelength, different methods are treated to sensitive wavelengths of each phenophase, and then hyperspectral parameters are built with them. Hyperspectral parameters and its correlation coefficients with nitrogen contents of apple leaves can be seen in Table 3.

Table 3 Hyperspectral parameters and its correlation coefficients with nitrogen contents of apple blades at different phenophases

Shoot growth phenophase		Spring shoots pause growth phenophase		Autumn shoots pause growth phenophase	
Hyperspectral parameters	Correlation coefficients	Hyperspectral parameters	Correlation coefficients	Hyperspectral parameters	Correlation coefficients
$R_{551}+R_{716}$	-0.8999**	$R_{543}+R_{705}$	-0.8416**	$R_{545}+R_{702}$	-0.7508**
$R_{551}-R_{716}$	0.5945**	$R_{543}-R_{705}$	0.6699**	$R_{545}-R_{702}$	0.4243**
$R_{551}*R_{716}$	-0.9000**	$R_{543}*R_{705}$	-0.8419**	$R_{545}*R_{702}$	-0.7512**
R_{551}/R_{716}	-0.8404**	R_{543}/R_{705}	0.2978*	R_{545}/R_{702}	0.1786
$(R_{551}+R_{716})/(R_{551}-R_{716})$	0.8408**	$(R_{543}+R_{705})/(R_{543}-R_{705})$	-0.3129*	$(R_{545}+R_{702})/(R_{545}-R_{702})$	-0.0922

$(R_{551}-R_{716})/(R_{551}+R_{716})$	-0.8400**	$(R_{543}-R_{705})/(R_{543}+R_{705})$	0.2953*	$(R_{545}-R_{702})/(R_{545}+R_{702})$	0.1822**
$FDR_{530}+FDR_{703}$	-0.8682**	$FDR_{699}+FDR_{756}$	-0.5689**	$FDR_{695}+FDR_{746}$	-0.4075**
$FDR_{530}-FDR_{703}$	0.6895**	$FDR_{699}-FDR_{756}$	-0.8240**	$FDR_{695}-FDR_{746}$	-0.7012**
$FDR_{530}*FDR_{703}$	-0.8726**	$FDR_{699}*FDR_{756}$	0.4628**	$FDR_{695}*FDR_{746}$	-0.4602**
FDR_{530}/FDR_{703}	-0.6315**	FDR_{699}/FDR_{756}	-0.6924**	FDR_{695}/FDR_{746}	-0.6623**
$(FDR_{530}+FDR_{703})/(FDR_{530}-FDR_{703})$	0.6332**	$(FDR_{699}+FDR_{756})/(FDR_{699}-FDR_{756})$	0.7124**	$(FDR_{695}+FDR_{746})/(FDR_{695}-FDR_{746})$	0.1119
$(FDR_{530}-FDR_{703})/(FDR_{530}+FDR_{703})$	-0.6300**	$(FDR_{699}-FDR_{756})/(FDR_{699}+FDR_{756})$	-0.7863**	$(FDR_{695}-FDR_{746})/(FDR_{695}+FDR_{746})$	-0.6954**

**: With a significance level of 0.01 *: With a significance level of 0.05

The estimation model of N content in apple leaves of three phenophases should be comparable, so each phenophase selects four hyperspectral parameters. Sequence by the size of the correlation coefficient, $R_{551}+R_{716}$, $R_{551}*R_{716}$, $FDR_{530}+FDR_{703}$, $FDR_{530}*FDR_{703}$ are caused in shoot growth phenophase, $R_{543}+R_{705}$, $R_{543}*R_{705}$, $FDR_{699}-FDR_{756}$, $(FDR_{699}-FDR_{756})/(FDR_{699}+FDR_{756})$ are chased in spring shoots pause growth phenophase, $R_{545}+R_{702}$, $R_{545}*R_{702}$, $FDR_{695}-FDR_{746}$, $(FDR_{695}-FDR_{746})/(FDR_{695}+FDR_{746})$ are caused in autumn shoots pause growth phenophase.

2.4 Establishing models for estimating N content of the apple tree leaves of different finishes

With the hyperspectral parameters selected, stepwise multiple linear regression models , partial least squares models and BP neural network models for estimating N content of the apple tree leaves at shoot growth phenophase, spring shoots pause growth phenophase, autumn shoots pause growth phenophase are established.

2.4.1 Establishing an estimation model using stepwise multiple linear regression method

Excluding variables forward and backward is combined with multiple linear regression analysis method. It will inspect all variables in the model after adding an independent variable and see if another independent variable could be excluded. After adding a new independent variable, the variable forward will be removed if its contribution of the variable forward to the model becomes not significant. In multiple linear regression analysis method, variable added before may be removed in next steps and the variable removed before may be added to the model in next steps (Jia et al., 2009). Multiple regression models were established with the sensitive parameters, and selecting the best model according to the principle of maximum R^2. The results can be seen in Table 4.

As shown in Table 4, the R2 of the multiple regression model $y=4.909-5.264x_1+3.009x_2+37.75x_3-21473.9x_4$ of shoot growth phenophase is 0.8364, parameter x_1, x_2, x_3, x_4 is $R_{551}+R_{716}$, $R_{551}*R_{716}$, $FDR_{530}+FDR_{703}$, $FDR_{530}*FDR_{703}$ respectively. The R^2 of the multiple regression model $y=3.830+7.954x_1-198.1x_2-140.9x_3-0.0277x_4$ of spring shoots pause growth phenophase is 0.7391, parameter x_1, x_2, x_3, x_4 is $R_{543}+R_{705}$, $R_{543}*R_{705}$, $FDR_{699}-FDR_{756}$, (FDR699-FDR756) /(FDR699+FDR756) respectively. The R2 of the multiple regression model $y=3.117-1.610x_1-28.28x_2-52.31x_3+0.1626x_4$ of autumn shoots pause growth phenophase is 0.5725, parameter x_1, x_2, x_3, x_4 is $R_{545}+R_{702}$, $R_{545}*R_{702}$, $FDR_{695}-FDR_{746}$,

(FDR_{695}-FDR_{746}) /(FDR_{695}+FDR_{746}) respectively. Shoot growth phenophase is more suitable to establish models for estimating N content of the apple tree leaves with hyperspectral parameters than other phenophases.

Table 4 Stepwise regression models for estimating nitrogen contents for apple leaves of the different growth phenophases

Growth phenophase	Hyperspectral parameters	Multiple stepwise regression models	R^2
Shoot growth phenophase	R_{551}+R_{716}, R_{551}*R_{716}, FDR_{530}+FDR_{703}, FDR_{530}*FDR_{703}	$y=4.909-5.264\ x_1+3.009\ x_2+37.75\ x_3-21473.9\ x_4$	0.8364
Spring shoots pause growth phenophase	R_{543}+R_{705}, R_{543}*R_{705}, FDR_{699}-FDR_{756}, (FDR_{699}-FDR_{756}) / (FDR_{699}+FDR_{756})	$y=3.830+7.954\ x_1-198.1\ x_2-140.9\ x_3-0.0277\ x_4$	0.7391
Autumn shoots pause growth phenophase	R_{545}+R_{702}, R_{545}*R_{702}, FDR_{695}-FDR_{746}, (FDR_{695}-FDR_{746}) / (FDR_{695}+FDR_{746})	$y=3.117-1.610\ x_1-28.28\ x_2-52.31\ x_3+0.1626\ x_4$	0.5725

2.4.2 Establishing an estimation model using partial least square method

Partial least squares method is a new multivariate data analysis submitted in applications, it has been rapidly developed in the past decade and many practical problems could be solved with it (Tang, 2010). PLS not only overcomes the multiple correlations between multiple dependent variables and multiple independent variables in traditional linear regression, but also adopts component extraction method. Component t1 and u1 are selected from independent variable **Error! Bookmark not defined.**adependent variable . Correlations of t1 and u1 reached the biggest and they would carry variability information of their data sheets as much as possible. The process will continue until the accuracy of the regression model reaches the best.

Partial least squares models are established with the 4 or 3 or 2 hyperspectral parameters of three phenophases respectively. In shoot growth phenophase, partial least squares models are established with four hyperspectral parameters (R_{551}+R_{716}, R_{551}*R_{716}, FDR_{530}+FDR_{703}, FDR_{530}*FDR_{703}), three hyperspectral parameters (R_{551}+R_{716}, R_{551}*R_{716}, FDR_{530}+FDR_{703}, FDR_{551}+FDR_{716}, R_{551}*R_{716}, FDR_{530}*FDR_{703}, R_{551}*R_{716}, FDR_{530}+FDR_{703}, FDR_{530}*FDR_{703} 和 R_{551}+R_{716}, FDR_{530}+FDR_{703}, FDR_{530}*FDR_{703}), two hyperspectral parameters (R_{551}+R_{716}, R_{551}*R_{716}, R_{551}+R_{716}, FDR_{530}+FDR_{703}, R_{551}+R_{716}, FDR_{530}*FDR_{703}, R_{551}*R_{716}, FDR_{530}+FDR_{703}, R_{551}*R_{716}, FDR_{530}*FDR_{703} 和 FDR_{530}+FDR_{703}, FDR_{530}*FDR_{703}). Partial least squares models of spring shoots pause growth phenophase and autumn shoots pause growth phenophase are established by the same method. The partial least squares models are selected with the biggest R^2 of each phenophase. The result can be seen in the Table 5.

As shown in Table 5, R^2 of shoot growth phenophase is bigger and the press of it is smaller, next is spring shoots pause growth phenophase and autumn shoots pause growth phenophase is the worst. It instructions that shoot growth phenophase is more suitable than other two phenophases to establish partial least squares models to estimate the N content in apple leaves.

Table 5 Simple linear models for estimating nitrogen contents for apple leaves of the different growth phenophases

Growth phenophases	Hyperspectral parameters	Partial least squares models	R^2	Press
Shoot growth phenophase	$R_{551}+R_{716}$, $R_{551}*R_{716}$, $FDR_{530}*FDR_{703}$	$y=4.511-2.258\ x_1-12.07\ x_2-13513.1\ x_3$	0.8348	10.15
Spring shoots pause growth phenophase	$R_{543}+R_{705}$, $R_{543}*R_{705}$, $FDR_{699}-FDR_{756}$	$y=5.241-6.230\ x_1-65.94\ x_2-111.9\ x_3$	0.7369	16.08
Autumn shoots pause growth phenophase	$R_{545}+R_{702}$, $R_{545}*R_{702}$, $FDR_{695}-FDR_{746}$	$y= 3.099-1.909\ x_1-20.37\ x_2-33.44\ x_3$	0.5711	26.20

2.4.3 Establishing an estimation model using a BP neural network method

Artificial neural networks are designed in accordance with people's research on biological neural networks. It is constituted by a series of neurons and their related links, it has a good mathematical description. It can be achieved by suitable electronic circuit, and it also can be simulated by the computer program memory conveniently (Jiang, 2001). The BP neural network is one of neural network models that widely used and it also be widely used in data fitting and simulation. 4-4-1,4-3-1and 4-2-1 BP neural network models are established in the study. From the fitting results of measured values and estimate values, the estimated effects of 4-3-1 BP neural network model is better than 4-4-1 and 4-2-1 BP neural network models. The fitting and comparison to the 4-3-1 BP neural network models of three phenophases are done with the data of second year. It found that the R^2 of shoot growth phenophase is bigger which is 0.6307, and spring shoots pause growth phenophase is smaller, which is 0.5454 and autumn shoots pause growth phenophase is in the middle which is 0.5979. It instructions that shoot growth phenophase is more suitable than other two phenophases to establish BP neural network models to estimate the N content in apple leaves.

2.5 The comparison of the models

Through the comparison of three kinds of estimation models established by hyperspectral parameters, it found that the R^2 of estimation models of shoot growth phenophase is bigger and autumn shoots pause growth phenophase is smaller and spring shoots pause growth phenophase is in the middle. The fitting and comparison in BP neural network models, it found the R^2 of shoot growth phenophase is bigger and spring shoots pause growth phenophase is smaller and autumn shoots pause growth phenophase is in the middle. So shoot growth phenophase is more suitable than other two phenophases to establish models to estimate the N content in apple leaves.

2.6 Examining the estimation models

To examine the stability and accuracy of the estimation model, taking the 60 sample data measured in shoot growth phenophase of the second year to examine the multiple regression model and partial least square model and BP neural network model for estimating the N content in apple leaves. The result of examination can be seen in Fig 3.

From Fig 3 we can see that the R^2 and RMSE and RE% of multiple regression models is 0.6135 and 28.26 and 0.7538 respectively. The R^2 and RMSE and RE% of partial least square model is 0.6074 and 27.88 and 0.7437 respectively. The R^2 and RMSE and RE% of 4-3-1 BP neural network model is 0.6307 and 23.37 and 0.6274 respectively. Through the comparison, it can be found that it found the R^2 of BP neural network model is bigger and partial least square model is smaller and multiple regression models is in the middle. Besides, the RMSE and RE% of the BP neural network model is smaller than the other two models. So, BP neural network model is the best model to estimate the N content in apple leaves.

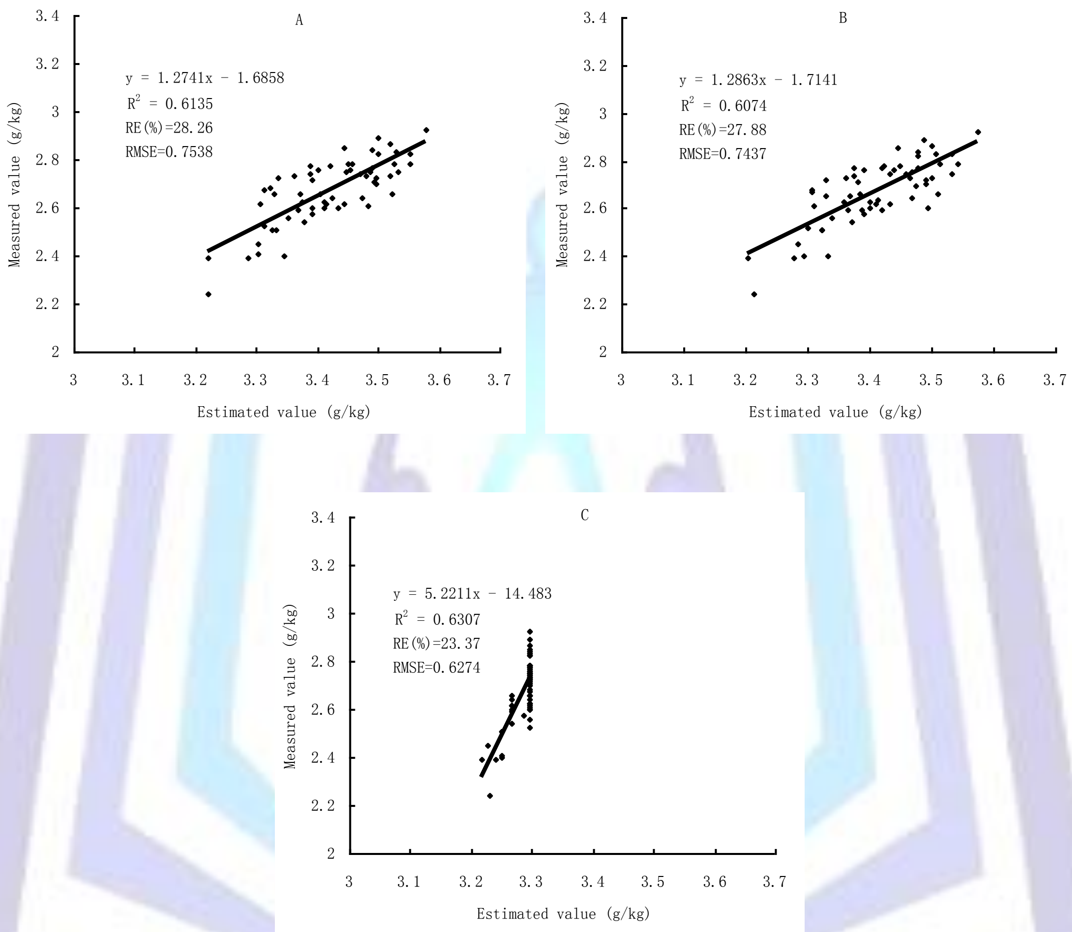


Fig.5 Comparison between the estimated value and measured value of nitrogen contents of apple leaves at Shoot growth phenophase

3 DISCUSSIONS

In the study of estimate the N content in apple leaves by hyperspectral parameter models, the majority of them are models with a single sensitive wavelength. Li Bingzhi et al. (2010) used the exponential model established by first derivative value at 723 nm as the prediction model for N content of apple leaves. Li Minxia et al. (2010) established estimation models for chlorophyll content and SPAD of apple leaves by first derivative value at 694 nm, and their R^2 reached 0.7817 and 0.5899. Chen Yizhao et al. (2010) established linear model for N content of Rubber leaves by reflectivity at 730 nm, and its multiple correlation coefficient reached 0.7094 [23]. These results are accurate and easy to do, but the sensitive wavelength selected may have a contingency. The hyperspectral parameters the study but are the combination of the reflectivity and first derivative value of sensitive wavelengths, they could avoid the contingency between the sensitive wavelengths and the N content of apple leaves, which make the models more reliable and practical.

Shoot growth phenophase is a critical period of apple trees for the conversion between newborn nutrition and stored nutrition. In this phenophase, the new shoots grow rapidly and leaves mature gradually. It is the best phenophase to measure N content of apple trees in the three phenophases. Of all the models of three phenophases, the effect of shoot growth phenophase is better. It proved that shoot growth phenophase has also been the phenophase to estimate the N content in apple leaves with hyperspectral technology.

In the analysis of the effect of the established models, the 4-3-1 BP neural network model of shoot growth phenophase has the best effect of estimation. The relationship between N content and hyperspectral of apple leaves may be not linear, so BP neural network model is more advantaged to estimate the N content than other linear models for it has both linear and nonlinear processing abilities.

The study used two years data on apple trees to establish models and analysis, whether the results have effect of many years apple trees of different phenophases steal need verification in future study.

4 CONCLUSIONS

The trend of spectral curves of the different phenophases of apple leaves is consistent, but in the visible range, the differences of reflectance between different phenophases are significant. The sensitive wavelengths of shoot growth phenophase are 551 nm、716 nm、530 nm and703 nm. The sensitive wavelengths of spring shoots pause growth phenophase are 543 nm、705 nm、699 nm and756 nm. The sensitive wavelengths of autumn shoots pause growth phenophase are 545 nm、702 nm 、695 nm and 746 nm. The hyperspectral parameters of each phenophase are $R_{551}+R_{716}$、$R_{551}*R_{716}$, $FDR_{530}+FDR_{703}$, $FDR_{530}*FDR_{703}$; $R_{543}+R_{705}$, $R_{543}*R_{705}$, $FDR_{699}+FDR_{756}$; $FDR_{699}*FDR_{756}$, $R_{545}+R_{702}$, $R_{545}*R_{702}$, $FDR_{695}+FDR_{746}$, $FDR_{695}*FDR_{746}$. stepwise multiple linear regression models , partial least squares models and BP neural network models for estimating N content of the apple tree leaves at each phenophase are established, and the 4-3-1 BP neural network model of shoot growth phenophase has the best effect of estimation. The study provides the basis for the further study of apple trees with hyperspectral data and has an important reference value of the research and practice in precision agriculture.

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