

# Winter wheat biomass estimation based on canopy spectra

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**Abstract:** The winter wheat aboveground biomass is an important agronomic parameter to estimate the growth status, and evaluate the yield and quality. Spectrum technique provides a nondestructive and fast method for estimating the winter wheat biomass. In order to find the optimum model by analyzing the wheat canopy spectral characteristic during the whole growth period, field trials were conducted at the National Demonstration Base of Precision Agriculture in Beijing Xiaotangshan town. A portable spectrometer (200-1100 nm) was used to collect the wheat canopy spectra of different varieties at the different growth stages (green stage, jointing stage, booting stage, heading stage and filling stage), clipping the winter wheat at ground level at the same time. Regression and correlation analysis were used to establish the winter wheat biomass estimation models in this study. The results showed that the biggest different bands of the winter wheat canopy spectral reflection curves mainly lied along the blue and near-infrared bands. The spectral reflectance at 678 nm in the visible light range had the best correlation with the biomass (correlation=0.724). The monadic regression analysis, the multiple regression analysis and the partial least squares regression analysis were applied to establish the biomass estimation models, among which the partial least squares regression (PLS) model had higher modeling precision. The  $R^2$  of the calibration and validation were 0.916 and 0.911, respectively. The root-mean-square error (RMSE) of the calibration and validation were 0.090 kg and 0.094 kg (Sample area 50 cm×60 cm). The results indicated that the PLS model (400-1000 nm) could fully estimate the aboveground biomass in the whole growth period of wheat with a better measurement accuracy.

**Keywords:** winter wheat, biomass, canopy spectra, crop growth period, partial least square regression

**DOI:** 10.3965/j.ijabe.20150806.1311

**Citation:** Zheng L, Zhu D Z, Liang D, Zhang B H, Wang C, Zhao C J. Winter wheat biomass estimation based on canopy spectra. Int J Agric & Biol Eng, 2015; 8(6): 30–36.

## 1 Introduction

The aboveground fresh biomass is an important index

**Received date:** 2014-06-19 **Accepted date:** 2015-10-10

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for crop growth, which can be the basic factor in detecting and estimating the yield of crop. Accurate estimation of crop biomass guides the early variable fertilization management in the field and predict yield later<sup>[1,2]</sup>. The traditional methods for getting the crop biomass require destructive sampling and weighing, which need a large amount of manpower and materials resources. It is time-consuming and cannot detect the crop growth in a large area effectively and timely, which is not conducive to make precise agriculture decision.

Many researches showed remote sensing technology could be used in the detection and estimation of various crop parameters, such as leaf area index (LAI), nitrogen content, chlorophyll content and moisture content<sup>[3-7]</sup>. Currently, the application of remote sensing technology

for monitoring crop growth and estimating the remote sensing model of crop biomass were realized mainly by making use of canopy spectral to establish vegetation index, seeking characteristic parameters of sensitive wave bands (red edge parameters) and using original wave bands directly. Some researchers adopted red edge parameters of rice and maize canopy spectral to estimate the weight of aboveground fresh biomass, and the correlation between them was significant<sup>[8,9]</sup>. Hansen et al.<sup>[10]</sup> and Casanova et al.<sup>[11]</sup> constructed vegetation index with spectral data to estimate the aboveground biomass and leaf area index (LAI) of wheat and rice, which showed a preferable correlation; Wang et al.<sup>[12]</sup> built hyperspectral vegetation indices and used artificial neural network to estimate the wheat biomass, compared with the traditional regression model, it had significantly improved the accuracy of wheat biomass estimation. The study of Song et al.<sup>[13]</sup> showed that a better power or exponential function was found between the ratio vegetation index (RVI) and the aboveground fresh biomass. It would become saturated to estimate the crop biomass for a certain range of biomass by using the common vegetation indices, such as the normalized difference vegetation index (NDVI), so that the crop biomass could not be estimated fully, and the accuracy of the model was low. In order to settle the problem of biomass saturation, Fu et al.<sup>[14]</sup> combined band depth characteristics of spectral data within the range of 550-750 nm with partial least squares method, which had improved the estimation accuracy in a certain extent ( $R^2=0.792$ ).

Although the saturation problem was solved to a certain extent, the estimate precision of biomass was still not high. Fu et al.<sup>[14]</sup> only used the spectral information in visible spectral domain (550-750 nm), a great deal of useful spectral information was not used. To this problem, this study made use of crop canopy spectral data actually measured (400-1000 nm) to analyze the correlation between the winter wheat aboveground biomass and the canopy spectral reflectance and red parameters, and established a detection model of winter wheat aboveground biomass through regression analysis and partial least squares method, so as to improve the monitoring capability to winter wheat aboveground fresh biomass and provide

scientific basis for the remote sensing monitoring in crop growth and precision agriculture.

## 2 Materials and methods

### 2.1 Field experiment

The experiment was conducted in Demonstration Base of Beijing Research Center for Information Technology in Agriculture, Xiaotangshan Town, Changping District, Beijing, from March to June, 2013. Zhongmai 12, Nongda 214, Zhongmai 175 and other 17 kinds of wheat varieties were adopted in this experiments, every variety was planted according to the normal density and half normal density. Each time, 40 plots with an area of 50 cm×60 cm were selected from 40 sample areas as test objects, and their canopy spectral reflectance and canopy image data were collected.

### 2.2 Spectra measuring method

AvaSpec-2048x14 Fiber Optic Spectrometer (Holland Avantes Company) was used in the acquisition of wheat canopy spectral reflectance data, the wavelength range measured was within the range of 200-1100 nm and the spectral resolution was 2.4 nm. The experiments were conducted in clear cloudless or partly cloudy days, which were March 28<sup>th</sup>, 2013 (returning green stage), April 11<sup>st</sup> (standing stage), April 25<sup>th</sup> (jointing stage), May 9<sup>th</sup> (heading stage), May 20<sup>th</sup> (flowering stage) and May 30<sup>th</sup> (filling stage) respectively, the specific time was from 10:30 to 14:30 (Beijing time), and spots with well-distributed population growth were selected. Optical fiber probe of the spectrometer was vertically downward, 75 cm away from the canopy of wheat leaves, standard reference plate correction was conducted every 15 min, each plot was measured 5 times and the average value was regarded as the spectral measuring result for each plot.

After completing the measurement of wheat spectral data and image data, destructive sampling was adopted by cutting off wheat close to the ground in measurement blocks. The fresh weight was measured by electronic scale with an accuracy of 0.5 g and a range of 5 kg.

All data processing and regression calculation were made in Excel, Matlab 9 and Unscrambler 7.8. A total number of samples were 239, 160 sets of data were

randomly selected as the calibration set for sample modeling; the remaining 79 samples were used as the validation set for model validation.

### 3 Results and discussion

#### 3.1 Variation of wheat canopy reflectance during the growing period

Figure 1 showed the canopy spectral reflectance curve of Jingdong 17 in different growth stages of winter wheat, which were the spectral reflectance in the stage of returning green, standing, jointing, heading, flowering and filling respectively. In Figure 1, since the plant continued to grow and the photosynthetic capacity enhanced constantly in the region of visible light, the ability of absorb blue and red light enhanced and the reflectance reduced gradually from the standing stage to jointing stage, and then to the heading stage. The absorption of winter wheat on green light was smaller than that on blue and red light, therefore, the reflectance of the green wavelength was bigger than those of blue and red light, which formed a small peak of reflectance. From the flowering stage to the filling stage, the reflectance decreased gradually as the chlorophyll of winter wheat decreased. Thus, in the region of visible light, the result showed that the canopy spectral reflectance of winter wheat decreased firstly and then increased at the different growth stage. In the near-infrared region, from returning green stage to the standing stage to the jointing stage, the chlorophyll increased with the continuous growth of the plant, due to which the canopy spectral reflectance in near-infrared increased continually. From the jointing to the heading stage, the canopy spectral reflectance reduced first and then increased, peaked at the flowering stage and then declined during the filling period, these results were consistent with previous studies<sup>[15-17]</sup>. The decline of reflectance in the later stages of growth might be caused by the structural change in the wheat canopy, the canopy structure included not only single leaf but ears and awns of wheat as well, and the variation of the chlorophyll content makes the reflectance in the near-infrared region dropped.

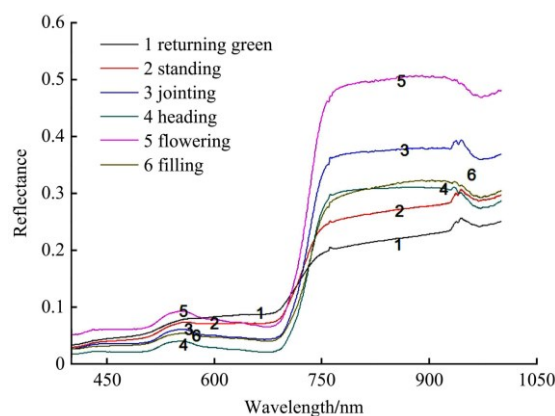


Figure 1 Canopy spectral reflectance of winter wheat at different growth stages

#### 3.2 Variation of the correlation between wheat biomass and canopy reflectance

By adopting the method of multivariate statistical analysis, the curve of correlation coefficients between the winter wheat biomass and the canopy spectral reflectance during the whole growth period was obtained (Figure 2).

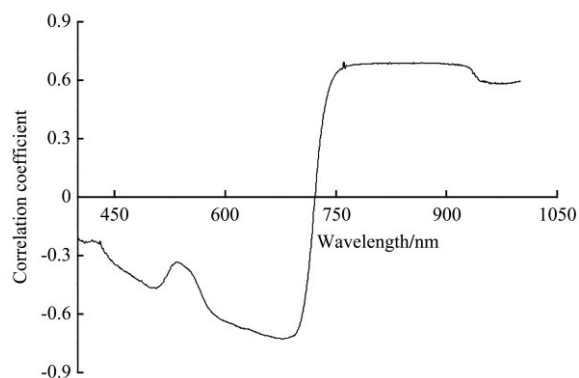


Figure 2 Correlation between the wheat biomass and spectrum

From Figure 2, during the whole growth period, the negative correlation between the canopy spectral reflectance and the wheat biomass exists within the wavelength range of 400-721 nm, in which, two troughs were formed within the range of 400-533 nm and 533-719 nm, the maximum value in correlation coefficients appeared in the wavelength of 505 nm and 678 nm, which were  $-0.465$  and  $-0.724$ , respectively; While the significant positive correlation between the canopy spectral reflectance and the winter wheat biomass existed within the wavelength range of 721-1050 nm, the correlation coefficient was relatively stable and maintained 0.68 from the wavelength of 760 nm; within the range of 680-750 nm, the correlation between the canopy spectral reflectance and the winter wheat biomass

changed greatly from negative to positive. According to the above analysis in correlation coefficients, the sensitive wavebands of the correlation between the winter wheat biomass and the canopy spectral reflectance were respectively at 505 nm, 678 nm and 760 nm.

### 3.3 Correlation between the red edge position of canopy reflectance and the wheat biomass

Due to the strong absorption of vegetation in the red light waveband and the strong reflection in the near-infrared waveband, the spectral reflectance showed a sharp increase within the wavelength of 680-750 nm. The “red edge” was the point of maximum slope of the vegetation reflectance curve with information characteristics, such as the red location and reflectance; therefore it became an important indicating waveband to describe of the pigment and health.

Hou et al.<sup>[18]</sup> established the index estimation model of the wheat dry biomass with the red edge amplitude, with good effectiveness, which indicated that the red edge amplitude could be used to predict the wheat dry biomass ( $R^2=0.669$ ). This study made use of this characteristic of continuous spectrum, analyzed the red edge parameters of canopy reflectance of winter wheat during the whole growth period and established a calibration model for the aboveground fresh biomass. The power function model constructed with red edge amplitude ( $D\lambda_{red}$ ) for the estimation of wheat aboveground fresh biomass had best determination coefficient and low error, which were  $R^2=0.773$  and  $RMSE=0.236$  kg. The fitting model was shown in Figure 3a. Using all of the remaining samples, a validation model was built with the power function model, as shown in Figure 3b.  $R^2$  in the validation model was 0.461,  $RMSE$  was 0.244 kg, which was not as good as the result of Hou et al.<sup>[18]</sup>. It might be because the fresh biomass was used in this text and Hou et al.<sup>[18]</sup> used the dry biomass. From Figure 3b, when the biomass was low, the fitting effect between measured value and predicted value was better, dispersing near the diagonal; while the biomass was high, the verification points were more dispersed. It showed that estimating wheat aboveground fresh biomass with red edge amplitude was more accurate during the earlier growth periods.

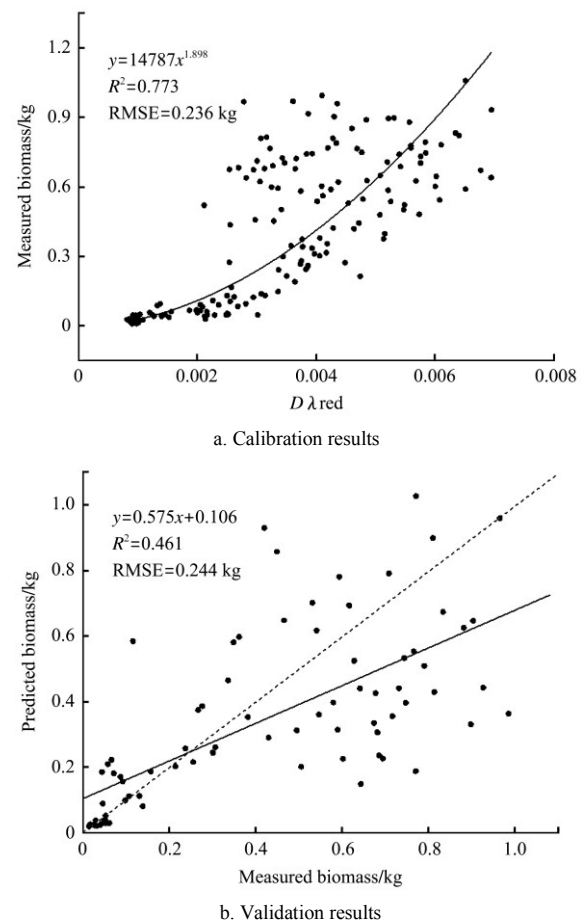


Figure 3 Regression results between  $D\lambda$  red and wheat biomass

### 3.4 Correlation between the biomass and the canopy reflectance with multiple linear regressions

According to the analysis results of the correlation between the wheat biomass and the canopy spectral reflectance within the growth period from Figure 2, the wavebands with maximal correlation in visible wavelengths and near-infrared wavebands were at 505 nm, 678 nm and 760 nm, so the multiple linear regression analysis between the winter wheat canopy spectral reflectance of these three wavebands and the wheat biomass was conducted. A calibration model for the wheat aboveground fresh biomass was established using the 160 groups of data from the calibration set, in which the multiple linear regression to analyze data is used.

The equation was as follows:

$$y=0.361+10.020x_1-10.350x_2+0.657x_3 \quad (1)$$

where,  $y$  was the wheat aboveground fresh biomass;  $x_1$  was the canopy spectral reflectance of 505 nm;  $x_2$  was the canopy spectral reflectance of 678 nm;  $x_3$  was the canopy spectral reflectance of 760 nm.

The determination coefficient  $R^2$  of biomass

calibration model was 0.674, RMSE was 0.179 kg and  $F$  was 0.000, which reached an extremely significant level. The above formula was used to predict the remaining samples and the result was shown in Figure 4,  $R^2$  of the validation model was 0.618 and RMSE was 0.188 kg. In Figure 4, the saturation phenomenon happened when the biomass reached 0.3 kg. Especially in the later growth periods, the error between the predicted value and the measured value became more significant. The feature band became less sensitive to the wheat aboveground fresh biomass, which affected the estimation accuracy of the wheat aboveground fresh biomass.

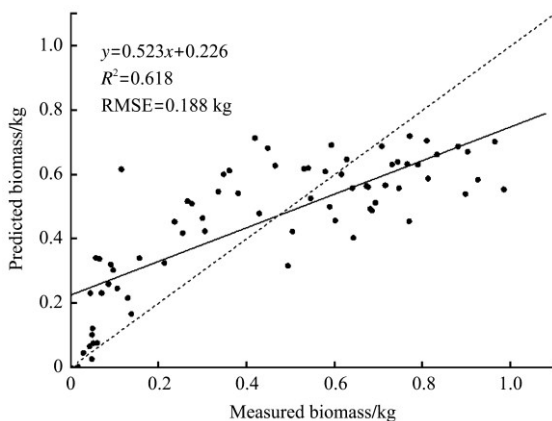


Figure 4 Relationship between measured biomass and predicted biomass by multiple linear regression

### 3.5 Correlation between wheat biomass and canopy reflectance with PLS

The partial least squares regression analysis (PLS) considered the integral association relationship between the independent variables set and dependent variables set. It integrated the multiple linear regression analysis, the canonical correlation analysis and the principal component analysis, which effectively overcame the difficulties that could not be solved by ordinary least squares regression analysis. A calibration model of winter wheat aboveground biomass was built with the method of partial least squares regression, using the 160 groups of data from the calibration set. The correlation analysis between the wheat aboveground fresh biomass and the canopy spectral reflectance within the waveband of 400-1000 nm was conducted using the partial least squares regression analysis. When the principal components number was 5, the result of the calibration model was the best with cross

validation method, of which the determination coefficient was 0.908, and the RMSE was 0.095 kg. The validation model was showed in Figure 5. The determination coefficient of the validation model built between the measured value and the predicted value was 0.911 during the whole growth period, and the RMSE was 0.094 kg. It had a higher accuracy than the model built from the canopy spectral indices<sup>[19,20]</sup>.

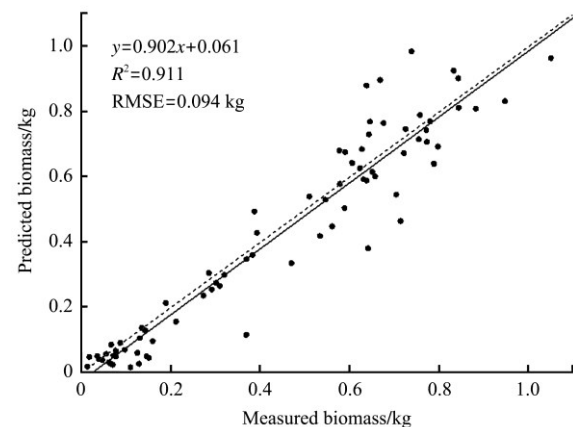


Figure 5 Relationship between measured biomass and predicted biomass by PLS

## 4 Conclusions

This study analyzed the trend of winter wheat aboveground fresh biomass and the canopy spectral reflectance characteristics from the returning greed stage to the filling period, and constructed the detection model for the winter wheat aboveground fresh biomass through the correlation analysis, the multiple regression analysis and the partial least squares regression analysis. The results were shown as follows: according to the correlation coefficient curve between the winter wheat aboveground fresh biomass and the canopy spectral reflectance, the sensitive wavebands of winter wheat aboveground fresh biomass were determined at 505 nm, 678 nm and 760 nm; the multiple linear regression analysis model of the wheat biomass was constructed with the canopy reflectance of sensitive wavebands, the determination coefficient of the validation model was 0.618, the RMSE was 0.188 kg; the determination coefficient of validation model constructed with red edge amplitude of the wheat aboveground fresh biomass was 0.461 and RMSEC was 0.244 kg; the saturation phenomenon happened in the multiple linear regression model and the power function model

constructed with red edge amplitude during the later growth periods, so they could not predict the biomass accurately; the detection model of winter wheat aboveground fresh biomass was constructed with the method of partial least squares regression analysis, the  $R^2$  of the calibration model was 0.916 and the RMSE was 0.090 kg, the  $R^2$  of the validation model was 0.911 and the RMSE was 0.094 kg, which were better than the model built in the multiple linear regression analysis and the power function model constructed with red edge parameters. The above results indicated that the prediction model constructed with the method of partial least squares regression analysis could detect the aboveground fresh biomass comprehensively and stably during the whole growth period of winter wheat, thus it can improve the accuracy of winter wheat aboveground fresh biomass estimation.

### Acknowledgment

This research was financially supported by Natural Science Foundation of China (31201125), Special Public Welfare Industry (Agriculture) research (201203026) and Beijing Municipal Natural Science Foundation (4142019).

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