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To link to this article:  http://dx.doi.org/10.1080/01431161.2016.1253899

Published online: 09 Nov 2016.

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Quantitative modelling for leaf nitrogen content of winter wheat using UAV-based hyperspectral data

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**ABSTRACT**
In this study, a big research progress has made in the research concerning leaf nitrogen content (LNC) nutritional spectral diagnosis on winter wheat at several growth stages, in which typical wave bands were put forward and quantitative models were constructed and validated. First, the unmanned aerial vehicle (UAV)-based hyperspectral data and the corresponding LNC data on winter wheat at several growth stages were obtained through experimenting in 2015, and the measured hyperspectral data and the LNC data were also obtained from the field-measured experimentation in 2014. Second, the spectral indices were calculated using UAV-based hyperspectral data and measured hyperspectral data, and the statistical regression models for diagnosing the LNC of different growth stages were constructed and analysed. Then, the correlation between the LNC and the spectral band is analysed. A method for selecting the typical bands of hyperspectral data responding to the LNC is proposed using spectral correlation as the basis. The UAV-based hyperspectral bands sensitive to the LNC of winter wheat are determined using this method. Finally, the hyperspectral quantitative models for diagnosing the LNC at the four stages are established by multifactor statistical regression and Back Propagation (BP) neural network methods. By comparing the modelling and verifying the coefficient, the UAV-based quantitative hyperspectral models’ effectiveness and practicability are then validated. The modelling results show that the predicted values are very ideal in jointing stage, flagging leaf stage, and flowering stage, while it is slightly less in the filling stage. The BP neural network modelling results were generally better than the multiple linear regression modelling results. This demonstrates that the effectiveness and spectrum sampling precision of UAV-based hyperspectral data are believable.

**ARTICLE HISTORY**
Received 4 April 2016
Accepted 21 October 2016

1. Introduction
The gradual application of remote sensing to agriculture has provided many scholars with a better understanding of the variations in the spectral characteristics of crops under different stress effects of water and fertilizer. Through remote sensing, plant
growth can be monitored in real time. For the past 10 years, hyperspectral remote sensing, which allows for high resolution, strong continuity, and massive information acquisition, has further promoted the development of quantitative agricultural remote sensing. Hyperspectral remote sensing has exhibited a considerable potential in the quantitative determination of plant nutrition and served as an important vehicle for the quantification of remote-sensing information and integrated qualification and mapping of thematic information on agriculture (Pu and Gong 1997; Qian and Pan 2004; Du and Chen 2003; Daniel and Gamon 2008). To date, many scholars, such as Yoder and Pettigrew (1995), Huang et al. (2004), Daniel and Gamon (2008), He, Liu, and Li (2014), and Li et al. (2014a, 2014b), have realized the hyperspectral detection of a large number of physiological and biochemical parameters of crops and vegetation, and achieved significant progress in hyperspectral remote-sensing applications, objects, methods, and contents. Schlerf and Atzberger (2006), Cho and Skidmore (2006), Zhang and Zhang (2008), Wang et al. (2010), Xia et al. (2013), He, Liu, and Li (2014), and Li et al. (2014a, 2014b) have proposed several methods for the quantitative inversion and detection of crop parameters based on spectral features.

Nitrogen is the most desired nutrient for plant growth, appreciably affecting the growth, development, and quality of crops. With the increase of nitrogen addition, the nitrogen content of plant canopy leaf reduces gradually. Under different nitrogen environments and fertilizer-N, the plant canopy leaf nitrogen nutrition will present different characteristics, which will affect the plants’ photosynthesis (Du et al. 2001; Poorter and Evans 1998; Hikosaka 2004; Li et al. 2014a). Leaf nitrogen content (LNC) is the major index for representing the plant’s leaf nitrogen nutrition, and through monitoring the LNC, proper fertilizer-N measures can be enacted. Crop parameters, such as leaf area index, biomass, chlorophyll content, and protein content, may vary with nitrogen content; as a result, the reflection spectra of the crop are affected (Curran 1989; Curran, Dungan, and Peterson 2001). With the progress in hyperspectral remote sensing, LNC can be monitored better and determined more accurately using the spectral information on crop canopy. Currently, some scholars have studied the crop nitrogen concentration estimating and monitoring model using hyperspectral data (Chen et al. 2010; He, Liu, and Li 2014; Feng et al. 2008; Erdle, Mistele, and Schmidhalter 2011; Zhang and Zhang 2008; Li et al. 2014b; Wang and Wei 2013).

At present, hyperspectral data can be either non-imaging or imaging. Non-imaging hyperspectral technology, by which hyperspectral data are acquired mainly using a ground spectrometer, has matured and has been widely applied to geology, agriculture, and other fields (Schlerf and Atzberger 2006; Kokaly and Clark 1999; Kokaly 2001). Hyperspectral imaging technology, which is usually satellite-borne or airborne, has more applications (Blackmer, Schepers, and Varvel 1994; Gong, Wang, and Liang 1999; Thenkaba, Smith, and Pauw 2000; Inoue and Peñuelas 2001; Tan et al. 2008; Wang et al. 2010; Dongyan et al., 2010). However, both types of technology have their respective limitations. Non-imaging ground survey can only acquire a modest amount of sampling points’ spectral information, and it cannot realize a rapid or efficient information acquisition of fertilizer-N in wide-ranging crops. Satellite-borne hyperspectral imaging technology has a long revisit period (usually approximately 30 days) and limited breadth. Satellite-borne hyperspectral imaging technology also encounters difficulties in continuously monitoring fertilizer-N, obtaining information on fertilizer-N in crops in fine-scale
plots, and meeting the requirements of precision agriculture applications because of its low spatial resolution (typically less than 30 m). Despite its mobility and flexibility, airborne hyperspectral imaging technology is subject to air traffic control and has high requirements in terms of light conditions; as a result, the cost of data acquisition based on this technology is high, and its wide-ranging applications in precision agriculture are restricted. Therefore, methods for acquiring the hyperspectral imaging data of crops and the accurate, timely, and dynamic quantitative estimation of fertilizer-N in crops are imperative. Such methods should be applicable to near-Earth low-altitude platforms for scale-suited plots.

Unmanned aerial vehicle (UAV)-based remote sensing can overcome the aforementioned drawbacks, because of its lower flight control, flexible and efficient use, and low operating cost and high spatial resolution. It has become a hotspot in the research and application of novel remote sensing (Cui and Sun 2004; Hong and Gong 2008; Zhou and Gong 2008). At present, hyperspectral imagery acquired from the UAV platform has been used for monitoring ground information and quantitative analysis (Saari et al. 2011; Hruska et al. 2012; Zarco-Tejada, González-Dugo, and Berni 2012; Lucieer et al. 2014).

In this study, a UAV mounted with a hyperspectral imaging device is used to acquire hyperspectral imaging data of the experimental plots of winter wheat (i.e. the subject). Quantitative hyperspectral detecting models for the LNC of winter wheat are developed. This study aims to promote the application of UAV-based hyperspectral remote sensing in precision agriculture.

2. Materials and methods

2.1 Experiment design

The experiment for this study was conducted in 2014 and 2015, for which the UAV data acquisition experiment was conducted in 2015 and ground data acquisition experiment was conducted in 2014. The study area is located in the National Demonstration Research Base of Precision Agriculture, which is located in the range of 40°10′31″N–40°11′18″N, 116°26′10″E–116°27′05″E and 36 m above sea level. The soil in the study area is moist, and the 0–0.3 m soil layer contains 3.16–14.82 mg kg\(^{-1}\) NO\(_3\)–, 15.8–20.0 g kg\(^{-1}\) available phosphorus, 3.14–21.18 mg kg\(^{-1}\) organic matter, and 86.83–120.62 mg kg\(^{-1}\) fast-acting potassium.

The winter wheat plot has an area of 150 m\(^2\) and has a total of 48 cells, which are planted with different winter wheat varieties under different water and fertilizer-N conditions. For significantly increasing the difference of winter wheat LNC, different N-fertilizer levels were set. Two winter wheat varieties (ZM175 and J9843), four gradients of fertilizer-N (N1, 0 kg of urea per ha; N2, 225 kg of urea per ha; N3, 450 kg of urea per ha; and N4, 900 kg of urea per ha), and three moisture levels (W1, rain-fed; W2, normally watered; and W3, watered twice as often as normally watered) were adopted for the experiment. The location of the experimental area and sample distribution is shown in Figure 1.
2.2 Experimental data

2.2.1 Hyperspectral imagery acquired from UAV

In this study, the UAV is an eight-rotor UAV, which was customized by SZ DJI Technology Co., Ltd China. The UAV’s machine weight is about 4 kg, and the maximum take-off weight is 11 kg. Its flight speed is 0–10 m s$^{-1}$, and the battery life is up to 15 min. High imaging spectrometer is UHD185, which is produced by the German Cubert company. Its spectral range is 450–950 nm, and the spectral resolution is 4 nm. The image ground resolution is 0.02 m. The experiments were carried on 15 April 2015, 26 April 2015, 12 May 2015, and 27 May 2015; these dates correspond to the four growth stages of winter wheat (jointing stage, flagging leaf stage, flowering stage, and filling stage).

About 3400 frames of UAV-based hyperspectral images data were acquired in every time of flight experiment and the data size is about 90 GB. Synchronously with UAV-based hyperspectral data acquisition, about 50 frames of digital photographs were also acquired in every time of flight experiment and are partly shown in Figure 2.
UAV-based hyperspectral data splicing and geometric correction processing were performed using the ground control points, which were obtained from UAV-based digital photographs, and the orthoimage of UAV-based hyperspectral data was produced. UAV-based hyperspectral data splicing and geometric correction processing used the cube-pilot software of UHD185 equipment. Finally, radiation correction processing for the orthoimage of the UAV-based hyperspectral data was carried out. Colour composite images of hyperspectral data corresponding to the four growth stages are shown in Figure 3.

The UAV-based hyperspectral image data is average processed according to the experimental range in 48 cells, and the hyperspectral data in every cell is obtained. High spectral quantitative analysis and the monitoring model for winter wheat LNC were conducted using these data.

2.2.2 Ground hyperspectral data acquisition
The ground hyperspectral data is acquired by the hyper-spectrometer, which is ASD FieldSpec Pro VNIR. For every cell, 20 spectral measurements of the wheat canopy were obtained; these measurements were then averaged to derive the spectral value of each sample, based on the results within the 450–950 nm spectral range. The experiments were carried out on 11 April 2014, 21 April 2014, 7 May 2014, and 20 May 2014; these dates correspond to the four growth stages of winter wheat (jointing stage, flagging leaf stage, flowering stage, and filling stage). Using these data, high spectral quantitative monitoring models for winter wheat LNC were tested, and the effectiveness and robustness of the model were analysed.

2.2.3 LNC data measured
Twenty winter wheat samples from each district were collected, synchronization with the hyperspectral data acquiring. After plant organ separation, the winter wheat leaf was dried at 80°C, and the LNC parameters (N %) were measured using the Kjeldahl
apparatus. The statistical values of LNC, which correspond to different growth periods and different nitrogen fertilizer levels, are listed in Table 1.

Statistics in Table 1 show that LNC takes on a trend of rising with increasing fertilizer-N rate in the growth period, and LNC of the filling stage was lower than that of the rest of the three stages. The dilution leads to LNC reducing in the process of crop growth (Graeff and Claupein 2003).

### 2.3 Research methods
#### 2.3.1 Spectral index
Spectral index refers to the combination of a certain band reflectance, which is related to the pigment of plant leaves, photosynthesis, and plant nutrition status. There are several spectral indices that could be used to estimate the plant LNC. In this study, three spectral indices, which have clear physical significance and have higher recognition, were selected for high spectral quantitative modelling for monitoring winter wheat LNC. The calculation method and literature sources of the four spectral indices are listed in Table 2.

<table>
<thead>
<tr>
<th>Spectral index name</th>
<th>Calculation method and literature sources of the spectral index</th>
</tr>
</thead>
<tbody>
<tr>
<td>−1 dB Ratio Index −1Db (RI)</td>
<td>$\frac{R_{735}}{R_{720}}$ (Gupta, Vijayan, and Prasad 2003)</td>
</tr>
<tr>
<td>Red edge normalized difference Vegetation index (RENDVI)</td>
<td>$(R_{730} - R_{705}) / (R_{730} + R_{705})$ (Sims and Gamon 2002)</td>
</tr>
<tr>
<td>Double-peak canopy nitrogen index (DPCNI)</td>
<td>$(R_{720} - R_{700}) / (R_{700} - R_{670}) / (R_{720} - R_{670} + 0.03)$ (Chen et al. 2010)</td>
</tr>
<tr>
<td>Normalized difference chlorophyll index (NDCI)</td>
<td>$(R_{762} - R_{527}) / (R_{762} + R_{527})$ (Ranjan et al. 2012)</td>
</tr>
</tbody>
</table>

### 2.3.2 Wavelength range dividing and typical band selecting
In this study, a method for dividing the hyperspectral wavelength range and obtaining the typical band corresponding to the wavelength range, which applies the autocorrelation matrix of spectral bands, is proposed. The procedure of the method is described as follows.

1. The correlation coefficient ($r$), which is a number that quantifies some type of correlation and dependence between two or more random variables or observed...
data values, between the measured LNC and the spectral reflectance of each band of the hyperspectral data, is calculated, and the band with the highest correlation is selected as the first typical band.

(2) The value of $r$ between the spectral bands is calculated, and the threshold of the $r$ value is set. And on this basis, the first wavelength range, which is represented by the first typical band, is obtained.

(3) Based on the bands corresponding to the first selected wavelength range boundaries and the threshold value of $r$, the second and third typical bands are obtained. The second and third wavelength ranges are further selected within the threshold value of $r$.

(4) The procedure is repeated until the entire hyperspectral wavelength range is covered.

Generally, the threshold value of $r$ setting is smaller, the wavelength range is larger, and the typical bands number is fewer.

2.3.3 Modelling methods
With the use of the regression statistical method, the quantitative monitoring models of LNC of winter wheat using spectral indices at different growth stages were established. Based on the Back Propagation (BP) neural network and the multivariate linear regression methods, the quantitative monitoring models of LNC using typical bands were established. The operation values of the quantitative models were calculated using the coefficient of determination ($R^2$) and the root mean square error (RMSE). Modelling and analysis are performed in Microsoft Excel 2010 and Matlab 2011.

3. Result and analysis
3.1 The quantitative models of spectral indices and LNC
Using the hyperspectral data of four growth stages of winter wheat, the spectral indices are calculated. Based on this, the linear and nonlinear regression statistical models, which simulate the quantitative relation of spectral indices and LNC, are obtained. The statistical models and the model coefficients are listed in Table 3. By using the ground hyperspectral data, the quantitative models for monitoring winter wheat LNC were verified, and the verification coefficients are listed in Table 3.

Table 3 depicts that the modelling results are consistent with the verifying results. This finding suggests that the UAV-based hyperspectral data and the ground measured hyperspectral data responding for LNC are consistent. The modelling result, which used the spectral indices, is better in the lag leaf stage and the filling stage, whereas it is poor in the jointing stage and the flowering stage. In the same growth period, different spectral index models’ coefficients and their verification coefficients are basically identical.

The analysis results show that the validity of the quantitative models of the LNC by using the spectral indices is greater in different growth periods, and thus the spectral index-sensitive response in different growth periods is different.
3.2 The hyperspectral wavelength range and the typical band of the four growth stages of winter wheat

3.2.1 Correlation coefficient result

The correlation coefficient \( r \) between the LNC and the spectral reflectance of each band of the hyperspectral data is calculated, and the results are shown in Figure 4.

As shown in Figure 4, the correlation between each measured LNC and the corresponding spectral band is from −0.72 to 0.66. A sharp rise is evident within the 690–750 nm wavelength range, which is the red edge band area. The maximum absolute value of \( r \) of the joint stage is 0.53, and the corresponding spectral band wavelength is 918 nm. The maximum absolute value of \( r \) of the flag leaf stage is −0.64, and the corresponding spectral band wavelength is 698 nm. The maximum absolute value of \( r \) of the flowering stage is −0.66, and the corresponding spectral band wavelength is 710 nm. The maximum absolute value of \( r \) of the filling stage is −0.72 and the corresponding spectral band wavelength is 570 nm.

The values of \( r \) of the spectral bands of the four growth stages are calculated and the results are shown in Figure 5.
As shown in Figure 5, the correlation between the adjacent bands in the hyperspectral data of LNC is high. As the wavelength range widens, the correlation decreases; the autocorrelation of the bands surrounding the central band is radically divergent and demonstrates significant boundary changes. For example, the
correlation between the 550 nm wavelength and its adjacent band is considerable and approximately 1. As the wavelength increases, the correlation between the 550 nm wavelength and the farthest 700 nm wavelength decreases. As the wavelength decreases, the correlation between the 550 nm wavelength and the 500 nm wavelength decreases sharply, resulting in significant boundary changes, as shown in Figure 5. Given that the correlation between the bands is high, considerable redundancy is evident in the information. Therefore, given that the threshold for the correlation between the bands is the basis for band selection, a band can be used to represent the bands within a range. Subsequently, typical bands are continuously selected based on the boundary band and the correlation threshold until the entire hyperspectral wavelength range is covered. Therefore, the information of the entire wavelength range is obtained by employing the information of as many typical bands as possible, considering the correlation of the bands and maximizing the use of hyperspectral band data.

3.2.2 The wavelength range and the corresponding typical band selection

With the threshold for the correlation between different bands set, the wavelength range and the corresponding typical band selection results can be obtained by the method described in Section 2.3.3. The thresholds for the correlation between different bands set are provided in the second column of Table 4. Moreover, in order to obtain the quantitative effect of typical band combinations reflecting the LNC, the multivariate linear fitting method was adopted to establish the quantitative model. In addition, the $R^2$ and the RMSE of the models are listed in Table 4.

According to the results in Table 4, in the jointing stage, when the threshold for the correlation between the bands is set to 0.95, the $R^2$ of the obtained quantitative model reaches the maximum with the minimal RMSE deviation. Therefore, wavelength ranges, such as 450–474 nm, 474–702 nm, 702–714 nm, 714–730 nm, and 730–950 nm, are selected, and the typical bands (466 nm, 690 nm, 710 nm, 718 nm, and 918 nm bands) are selected. In the flag leaf stage, when the threshold for the correlation between the bands is set to 0.9, the $R^2$ of the obtained quantitative model reaches the maximum with the minimal RMSE deviation. Therefore, wavelength ranges, such as 450–462 nm, 462–714 nm, 714–738 nm, and 738–950 nm, are selected, and the typical bands (462 nm, 698 nm, 722 nm, and 754 nm bands) are selected. In the flowering stage, when the threshold for the correlation between the bands is set to 0.95, the $R^2$ of the obtained quantitative model reaches the maximum with the minimal RMSE deviation. Therefore, wavelength ranges, such as 450–698 nm, 698–726 nm, 726–734 nm, 734–746 nm, and 746–950 nm, are selected, and the typical bands (462 nm, 698 nm, 722 nm, and 754 nm bands) are selected. In the filling stage, when the threshold for the correlation between bands is set to 0.95, the $R^2$ of the obtained quantitative model reaches the maximum with the minimal RMSE deviation. Therefore, wavelength ranges, such as 450–462 nm, 462–718 nm, 718–726 nm, 730–758 nm, and 758–950 nm, are selected, and the typical bands (458 nm, 570 nm, 722 nm, 734 nm, and 758 nm bands) are selected.

In addition, the typical band combinations, such as (690 nm, 710 nm, 718 nm), (698 nm, 722 nm, 754 nm), (710 nm, 730 nm, 738 nm, 746 nm), and (722 nm, 734 nm, 758 nm), which correspond to the jointing stage, the flagging leaf stage, the flowering
Table 4. Results of high spectral wavelength range and typical band selection.

<table>
<thead>
<tr>
<th>Growth stages of winter wheat</th>
<th>Values setting of correlation coefficient threshold</th>
<th>Wavelength range (nm) results corresponding to the correlation coefficient thresholds</th>
<th>Typical bands (nm) corresponding results to the wavelength ranges</th>
<th>Statistical coefficients of the multivariate linear model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Jointing stage</td>
<td>0.6 (450–698), (698–730), (730–950)</td>
<td>698, 718, 918</td>
<td>0.461 0.389</td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.65 (450–702), (702–730), (730–950)</td>
<td>702, 718, 918</td>
<td>0.461 0.389</td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.7 (450–710), (710–730), (730–950)</td>
<td>710, 722, 918</td>
<td>0.450 0.394</td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.75 (450–710), (710–730), (730–950)</td>
<td>710, 722, 918</td>
<td>0.450 0.394</td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.8 (450–718), (718–734), (734–950)</td>
<td>706, 726, 918</td>
<td>0.452 0.393</td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.85 (450–702), (702–722), (722–734), (734–950)</td>
<td>702, 714, 726, 918</td>
<td>0.454 0.392</td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.9 (450–698), (698–718), (718–726), (726–738), (738–950)</td>
<td>698, 710, 722, 730, 918</td>
<td>0.518 0.368</td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.95 (450–474), (474–702), (702–714), (714–742), (742–950)</td>
<td>466, 690, 710, 718, 918</td>
<td>0.658 0.312</td>
<td></td>
</tr>
<tr>
<td>Flag leaf stage</td>
<td>0.6 (450–722), (722–950)</td>
<td>698, 738</td>
<td>0.502 0.340</td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.65 (450–722), (722–950)</td>
<td>698, 738</td>
<td>0.502 0.340</td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.7 (450–722), (722–950)</td>
<td>698, 738</td>
<td>0.502 0.340</td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.75 (450–718), (718–742), (742–950)</td>
<td>698, 730, 742</td>
<td>0.634 0.292</td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.8 (450–718), (718–742), (742–950)</td>
<td>698, 730, 742</td>
<td>0.634 0.292</td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.85 (450–714), (714–734), (734–950)</td>
<td>698,726, 746</td>
<td>0.636 0.291</td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.9 (450–462), (462–714), (714–738), (738–950)</td>
<td>462, 698, 722, 754</td>
<td>0.863 0.179</td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.95 (450–460), (460–710), (710–722), (722–730), (730–738), (738–950)</td>
<td>454, 698, 718, 726, 734, 754</td>
<td>0.860 0.178</td>
<td></td>
</tr>
<tr>
<td>Flowering stage</td>
<td>0.6 (450–726), (726–950)</td>
<td>710, 738</td>
<td>0.511 0.302</td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.65 (450–726), (726–950)</td>
<td>710, 738</td>
<td>0.511 0.302</td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.7 (450–726), (726–950)</td>
<td>710, 738</td>
<td>0.511 0.302</td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.75 (450–722), (722–738), (738–950)</td>
<td>710, 730, 738</td>
<td>0.629 0.263</td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.8 (450–722), (722–738), (738–950)</td>
<td>710, 730, 738</td>
<td>0.629 0.263</td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.85 (450–722), (722–730), (730–742), (742–950)</td>
<td>710, 726, 734, 742</td>
<td>0.687 0.242</td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.9 (450–718), (718–726), (726–734), (734–950)</td>
<td>710, 722, 730, 742</td>
<td>0.679 0.245</td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.95 (450–698), (698–726), (726–734), (734–746), (746–950)</td>
<td>474, 710, 730, 738, 746</td>
<td>0.861 0.161</td>
<td></td>
</tr>
<tr>
<td>Filling stage</td>
<td>0.6 (450–726), (726–754), (754–950)</td>
<td>570, 734, 754</td>
<td>0.582 0.435</td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.65 (450–726), (726–754), (754–950)</td>
<td>570, 726, 750</td>
<td>0.582 0.435</td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.7 (450–726), (726–754), (754–950)</td>
<td>570, 726, 750</td>
<td>0.582 0.435</td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.75 (450–726), (726–754), (754–950)</td>
<td>570, 726, 750</td>
<td>0.582 0.435</td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.8 (450–726), (726–754), (754–950)</td>
<td>570, 726, 750</td>
<td>0.582 0.435</td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.85 (450–722), (722–730), (730–738), (738–950)</td>
<td>570, 726, 734, 750</td>
<td>0.586 0.423</td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.9 (450–722), (722–730), (730–746), (746–950)</td>
<td>570, 726, 738, 746</td>
<td>0.585 0.426</td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.95 (450–462), (462–718), (718–726), (726–758), (758–950)</td>
<td>458, 570, 722, 734, 758</td>
<td>0.661 0.393</td>
<td></td>
</tr>
</tbody>
</table>

stage, and the filling stage, are concentrated in the red band and along the boundary line in the red band, which are significantly associated with LNC. The bands, such as 466 nm, 462 nm, 474 nm, and 458 nm, are blue bands sensitive to the vegetation index. Therefore, the derived hyperspectral band variables of the quantitative models for the LNC of winter wheat are theoretically accurate.
3.3 Establishment and analysis of the quantitative model

In this study, the quantitative models of each growing period, which simulate the typical band combination with winter wheat LNC, were established by using the multiple linear regression and BP neural network methods. Meanwhile, the results of the models were contrastively analysed using the ground measured hyperspectral data, and the results are listed in Table 5. Among them, the neurons parameter of the BP neural network modelling and verifying was 20.

Through analysing the modelling results, we can see that the modelling and validation results by two different modelling methods are all ideal, and the BP neural network modelling results were generally better than the multiple linear regression modelling results. The models of the flag leaf stage and the flowering stage were better than those of jointing the stage and the filling stage. The verification results of the model were found to be superior to the modelling results by analysing the $R^2$ and RMSE parameters. The analysis results show that the typical bands responding for the winter wheat LNC were comparatively accurate, and the established models using UAV-based hyperspectral data are credible and effective.

<table>
<thead>
<tr>
<th>Table 5. Results of representative band modelling.</th>
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<tr>
<td>The growth period and the corresponding typical bands (nm) of winter wheat</td>
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<tr>
<td>Jointing stage (466, 690, 710, 718, 918)</td>
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<tr>
<td>Flag leaf stage (462, 698, 722, 754)</td>
</tr>
<tr>
<td>Flowering stage (474, 710, 730, 738, 746)</td>
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<tr>
<td>Flowering stage (458, 570, 722, 734, 758)</td>
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</table>

4. Discussion

4.1 Quantitative modelling of LNC using the spectral indices

The linear and nonlinear statistical models that simulate the quantitative relation of spectral indices and LNC are obtained, and the modelling result shows that the UAV-based hyperspectral data and the ground measured hyperspectral data for estimating the LNC result are consistent. In the same growth period, different spectral index model coefficients and their verification coefficients are basically identical. The modelling results suggest that the spectral index is unsatisfactory for sensitively estimating the LNC of winter wheat, and spectral bands that are included in the spectral index have a lower level of response for the LNC of winter wheat.

4.2 The difference of typical bands of different growth periods

The typical bands of the four growth periods of winter wheat are shown in Figure 6.
Through analysing Figure 6, we can see that the spectral bands responding for LNC are mostly concentrated in the range of red and blue wavelengths, especially the concentrated neighbourhood of the red edge position (690–800 nm). Thus, the typical bands mainly locate in the blue and red light wavelength ranges, but the specific band is different at different growth stages of winter wheat. The total number of typical bands is 19, and there are 13 typical bands that distribute in the neighbourhood of the red edge position. In each growth stage of winter wheat, more than 50% within the scope of typical bands is located in the neighbourhood of the red edge. Therefore, the results fully confirm that there is a strong spectrum response in the red edge range for the LNC of winter wheat.

4.3 The discussion of quantitative models

By applying the quantitative model established using the UAV-based hyperspectral data, the prediction results are obtained using the ground measured hyperspectral data. The prediction results and the corresponding measured results of LNC of each growth stage of winter wheat are shown as Figures 7–10. And the $r$ value of the
prediction results and the corresponding measured results of LNC are also calculated, which are shown in Figures 7–10.

The modelling results show that the predicted values are very ideal in the jointing stage, the flag leaf stage, and the flowering stage, whereas it is slightly less in the filling stage. The BP neural network modelling results were generally better than the multiple linear regression modelling results. These suggest that the effectiveness and spectrum sampling precision of UAV-based hyperspectral data are higher.
In addition, in the jointing stage of winter wheat, the leaf area index is smaller and the plant community coverage is lower, and canopy spectral reflectance is susceptible to the influence of soil background. In the flag leaf period and the flowering period, the leaf area index increases gradually and the canopy group is relatively closed, so the biomass of winter wheat organs accumulates gradually. From the filling stage to the mature stage, winter wheat turns into the reproductive growth period, and the leaf area index decreases and the content of chlorophyll gradually reduces. The difference of the spectrum quantitatively responding for LNC is determined by the canopy changes characteristics in winter wheat growth.

5. Conclusion

In this study, the UAV-based hyperspectral data and the measured LNC data of winter wheat at several growth stages are obtained through experiments conducted in 2015. The ground measured hyperspectral data and the LNCs data are also obtained from the field-measured experimentation on the experimental plot of winter wheat in 2014. Based on UAV-based hyperspectral data and measured LNC data, the correlation between the LNC of winter wheat and the spectral band is analysed. A method for selecting the typical bands of hyperspectral data for diagnosing the LNC of winter wheat is proposed using spectral correlation as the basis. The spectral bands sensitive to the LNC of winter wheat are determined using this method. The hyperspectral quantitative models for monitoring the LNC of winter wheat at the four stages are established by statistical regression and BP neural network methods. Next, the models are validated and analysed. At the same time, the typical band characteristics of the quantitative models have been carried out on the preliminary analysis.

The selection of typical bands is based on UAV-based hyperspectral image data and the autocorrelation threshold for the fixed band. The experimental results show that the LNC regression model using the selected typical bands completely meets the pertinent requirements. However, further investigation is required to determine whether the entire hyperspectral wavelength range can be covered with fewer bands by adaptively selecting the band correlation threshold based on the curve of the correlation between the LNC and the band. Moreover, the applicability of the quantitative model using the selected sensitive bands to the monitoring of other
crops and biomass also requires further analysis and verification with the use of additional experimental data.

**Acknowledgements**

This work was supported by the auspices of the National Natural Science Foundation of China (Nos. 41471331, 41601408, 41376108, 41301422).

**Disclosure statement**

No potential conflict of interest was reported by the authors.

**Funding**

This work was supported by the National Natural Science Foundation of China [Grant Numbers: 41471331; 41601408; 41376108; 41301422].

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