SIMULATION OF SOYBEAN CANOPY NUTRIENT CONTENTS BY HYPERSPECTRAL REMOTE SENSING

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Abstract. Precision fertilizer management could help reduce farming costs and maintain production sustainability in current cropping systems. Soybean is a major oil crop and to improve temporal and spatial fertilizer application to demand variations, soybean canopy nutrient status was diagnosed by the hyperspectral remote sensing techonology. First, field canopy spectral reflectance was characterized during key developmental stages with three levels of fertilizer treatments in northeastern China. Then, foliar nitrogen (N), phosphorus (P) and potassium (K) contents were quantified and analyzed for correlation with transformed spectral data formats including reciprocal, logarithm and derivatives, red edge parameters and vegetation index. Last, simulation models for soybean canopy nutrient status (total N, P and K) were constructed. The simulation model (y= -19.153x+3.1114) using second derivatives of spectral data at 432 nm was proved to significantly correlate the predicted value with measured total N content (r=-0.7829, p<0.01; RE=0.1713). The first derivative-derived models y=-0.2939x+0.5889(r=-0.6172, p<0.01; RE=0.2428) at 909 nm and y=-0.4157x+1.874(r=-0.5631, p<0.01; RE=0.1345) at 908 nm produced most accurate prediction for total P and K respectively. Models reported in this work were top selections for the simplicity and practicality in predicting soybean nutrient and growth status.
Keywords: *soybean, nutritional status, predictive modeling, remote sensing, canopy reflectance*

Introduction

To meet increasing needs of food supply from the fast growing global population, high cropping yields have to be achieved and be even further increased. Since plant growth, development and productivity depend on the availability of nutrients, intensive use of fertilizers has become common agronomic practices of current farming systems especially in low productive regions. However, excessive application of fertilizers has caused major detrimental impacts on the ecosystem and increased costs for both producers and consumers. In this regard, there is a clear need of more reasonable and "intelligent" use of fertilizers to help maintain environmental and economic sustainability of the agricultural production (Chen et al., 2014), which is a main aspect of precision agriculture (PA) (Gebbers and Adamchuk, 2010). Precision fertilization allows a finer degree of fertilization responding to intra-field variability in crops such as different soil conditions and the "heterogeneous" plant growth status so that fertilization efficiency can be improved and productivity is "intensified" (Lindblom et al., 2017).

Plant growth status can be reflected by outward structural characteristics and internal chemical compositions. Hyperspectral remote sensing is a technology used for the collection of information of contiguous high-resolution electromagnetic radiation emitted from an object so that to recognize and locate the target and reveal its natural properties. In recent years, the hyperspectral agricultural remote sensing technology has been used to

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predict crop water content (Holben et al., 1983; Su et al., 2010; Liu et al., 2012), chlorophyll content (Madeira et al., 2000; Tang et al., 2011; Curran et al., 1999), leaf surface area index (Bouman et al., 1992; Danson and Plummer, 1995; Feng et al., 2009) and other biophysical parameters (Vergara-Díaz et al., 2016) and major nutrient elements of plants (Femandez et al., 1994; Cheng et al., 2011; Yi et al., 2014), monitoring micronutrient and other nutrient status of crops (Masoni et al., 1996; Wang et al., 2012).

A combination of techniques suitable for remotely sensing foliar Nitrogen (N) in semiarid shrublands – a capability that would significantly improve our limited understanding of vegetation functionality in dryland ecosystems (Mitchell et al., 2012). In A. Zerger study introduced that environmental sensor networks for vegetation, animal and soil sciences (Zerger et al., 2010). The ratio vegetation index (RVI) between the spectral reflectance from the near-infrared and visible band ranges can be used to construct a hyperspectral simulation model for soybean leaf area index (Zhang et al., 2005). Advance on application of of hyperapectral technology in detection of crop was proposed (Liu et al., 2013). Findings from these large numbers of research efforts have provided the theoretical bases for incorporating the remote sensing technology in precision fertilization by diagnosing plant nutrient status.

Crop species each may have its own characteristic spectrum; the information from visible light, near infrared light, and short infrared region can be used to produce biomass at high accuracy (Shibayama et al., 1989). Study by a Chinese group discovered that in a soybean crop, the above-ground fresh weight has a strong correlation with the spectral signatures in the range of 760~1050nm, and RVI can be used to accurately predict soybean above-ground biomass yield (Song et al., 2005; Chen et al., 2010). The canopy reflectance indices measured at early flower stage of cotton growth could serve as input to a crop growth model for predicting potential yield loss (Zhao et al., 2007).

Chlorophyll content and leaf spectral characteristics have a very strong correlation (Madeira et al., 2000). Studies found that soybean chlorophyll A, B contents have a negative relationship with canopy reflectance in the visible band range, and in the near-infrared wavelength, and it changed to positive in the red edge band region (Song et al., 2006). At 536, 577, 611, 680, 705 nm wavelengths, the first derivative of spectral reflectance has a significant correlation with chlorophyll content (Chen et al., 2012). In Tang study proposed to use the Neural Network Model to estimate stable soybean canopy chlorophyll content.

Spectral measurements are useful for estimating the nitrogen status of crops, thereby enabling site-specific fertilizing in precision farming systems (Mistele and Schmidhalter, 2008). Soybean is one of the most cultivated oil crop worldwide and especially in northeastern regions of China in terms of land area and production (Zhang et al., 2014). Presently, spectral remote sensing technology is mainly used in soybean field to analyze biomass yield, leaf surface area and chlorophyll content. Plant nutrient diagnosis studies, in particular of P and K, have not been investigated. In this study, the technology and theory in remote sensing and the ground remote sensing were applied to develop models for the evaluation of soybean plants, in combination with the hyperspectral non-invasive monitoring technology and field data synchronization collection method, and with the aid of statistical analysis methods. The objective was to explore the major agronomic parameters, and leaf nutrient contents, and its relationship with reflectance spectrum. The characteristic spectral signatures were extracted for each plant growth parameter, and to construct simulation models for plant growth using

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canopy reflectance spectral data. Findings from this study will provide theoretical bases for real time diagnosis and accurate management of soybean fields in Northeast China.

Materials and Methods

Materials and Experimental Design

The experiment was performed on the experimental station at Shenyang, China (41°48′11.75″N, 123°25′31.18″E) in 2013. The soil of experimental sites were similar typical cropping soil in northeastern China which contained a total content of 2.65 g kg^{-1} N, 0.083 g kg^{-1} P, 75 mg kg^{-1} alkali-hydrolysable nitrogen, 0.07 mg kg^{-1} available P, 149.56 mg kg^{-1} available K, 18 g kg^{-1} organic matter. Liaoning No.14, a semi-determinate and Liaoning No.15, a determinate cultivar were chosen as experimental varieties. Seeds were sown on the 18^{th} of Maywith a density of 165, 000 plants hm^{-2}. Three P levels (P_2O_5), at 0, 5.5, 11 kg hm^{-2}, were designated as P0, P1, P2 respectively. Each plot (L 7 m x W 4 m) was used for one soybean variety with one P treatment. Every variety and treatment combination was repeated for three times and the total eighteen plots were randomly arranged. The same field management procedures were adopted for all experiments.

Collection of canopy spectral data

A portable spectrometer (ASD, USA) was used to collect canopy spectral reflectance. The instrument was operated with a 512 *element photo-diode array* (PDA) probe within wavelength spectrum of 325 ~ 1075 nm. The scanning was conducted according to the operational instruction for ASD as: spectral resolution was 3 nm; scan time interval was 17 ms; spectral sampling interval was 1.5 nm; the probe was placed vertically over the canopy at a field angle of 10°; the distance from probe to the top of the canopy was 1 m. The instrument was calibrated against internal reference prior to each measurement. Measurements were taken during key soybean developmental stages including branching, early flowering, peak flowering, pod setting and seed bulging stages. To control variation from field conditions, measurements were only taken on sunny days from 10 AM to 14 PM (local time). Each spectral reflectance data was an average of twenty measurements on a single plot.

Analysis of N, P and K contents in soybean leaves

After taking spectral measurements, fully expended leaves from the canopy top were cut without petiole and frozen immediately in liquid nitrogen. On each plot, twelve leaves collected from six plants were oven-dried (105 °C for 0.5 hour followed by 80°C for 2 days) then ground into fine powder for mineral content analysis. Sample digestion was carried out using the H_2SO_4-H_2O_2 method. The total nitrogen content was quantified using the classic Kjeldahl method. The total P content was quantified using the Mo-Sb- Vc- colorimetric method and the atomic absorption spectroscopy was used for K quantification.

(Leaf area index was measured but not included in this manuscript.)

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Processing of spectral data

(1). The first and second derivative spectrum

The reflectance spectra were transformed into the first derivative spectral revalues using the following equation:

$$\rho'(\lambda_1) = [\rho(\lambda_{i+1}) - \rho(\lambda_{i-1})]/2\Delta\lambda \quad \text{(Eq.1)}$$

λ_i is the wavelength of each channel (band); $\rho'(\lambda_i)$ is the first derivative spectrum of each band;

$\Delta\lambda$ is the interval difference from λ_{i-1} to λ_i

The second derivative spectrum was calculated by using the first derivatives as input data into the above equation.

(2). Calculation of red edge parameters

The red edge parameters were calculated for bands corresponding to the first derivative spectrum maximum within the red edge range (680 ~ 760 nm). The red edge slope is the first derivative spectra collected from the maximum peak area in the red edge range (680 ~ 760 nm). The red edge peak area is the size of the area surrounded by the first derivative spectra in the 680 ~ 760 nm range.

(3). Calculation of common vegetation indices

Common vegetation indices were calculated according to equations listed in the *Table 1*.

Table 1. *Formula for calculating common vegetation indices.*

Index	Abbreviation	Equation	Reference
Ratio vegetation index	RV	$RVI = \frac{\rho_{NIR}}{\rho_{RED}}$	Pearson et al.（1972）
Difference vegetation index	DVI	$DVI = \rho_{NIR} - \rho_{RED}$	Jordan（1969）
Normalized difference vegetation index	NDVI	$NDVI = \frac{\rho_{NIR} - \rho_{RED}}{\rho_{NIR} + \rho_{RED}} = \frac{RVI - 1}{RVI + 1}$	Rouse et al.（1974）
Re-normalized difference vegetation index	RDVI	$RDVI = \sqrt{NDVI \times DVI}$	Reujean and Breon（1995）

Model simulation

A canopy spectural reflectance data set was input with leaf N content data (from all examined soybean developmental stages) into the EXCEL software to calculate for associated factors across the whole scanning spectrum. The data reflectance data format with highest associated factors was chosen for model construction. The wavelength corresponding to the highest associated factor was chosen as characteristic wavelength to nutrient N. Then, a linear regression model was constructed in EXCEL with the chosen format of data set on the characteristic wavelength. Simulation models for P and K were constructed with the same protocol.

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Software tools

All vegetation indices were calculated with a self-programmed software. All other data processing and analysis were performed with the the EXCEL software.

Results and analysis

Changes of soybean canopy reflectance spectrum at different growth stages

The structure and physiological properties of soybean canopy change as plants grow, and those alterations will affect characteristics of the canopy spectral reflectance. When examining the whole spectral curve in the visible light range of 400~680 nm, it was found that the highest reflectance occurred at the branching stage, it then declined and stabilized at a lower level during seed bulging and maturation stages (*Fig. 1*). This spectral band region is influenced strongly by plant pigments. It is possible that as soybean plants grow, leave accumulate more chlorophyll thus increasing the absorbance capacity for visible light. The same physiological state continues until pod-set stage. Thereafter, plant pigment content gradually declines to a stable low level, thus spectral reflectance rate also stabilizes at a different level. In the near-infrared region (760~1000 nm), the reflectance rate also changed significantly with plant growth. The canopy spectral reflectance was at the highest level at the branching stage. At more mature growth stage, the reflectance rate gradually decreased till reaching the lowest level at the maturation stage (*Fig. 1*). Furthermore, it was also found that from flowering to seed set period, and from seed bulging and maturation period, the spectral reflectance curve had several big fluctuations. It is likely that during the first period from flowering to seed set stages, large amounts of leaf mineral nutrients were transported to seed pods, and then during the second period from seed bulging to maturation stages, plants started to age and deteriorate resulting in physiological functional decline.

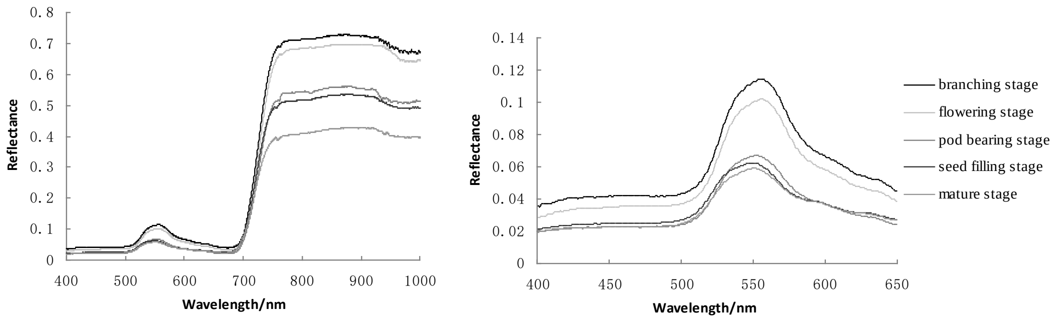

Figure 1. *Hyperspectral reflectance of soybean at different growth stages*

Characteristic changes in soybean canopy total N, P K contents

Changes of soybean leaf mineral nutrients at different growth stages were shown in *Fig. 2*. The total N content decreased as plants grew with a sharp decline from branching to flowering stages then it slowed down at the post-flowering stage. Contents of P and N seem to have positive synergistic effects. The application of P fertilizer treatment had a positive effect on N content. For plants passed the flowering stage, leaf P content was higher for the one that were fed with P fertilizers than those without P

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fertilizers; P-1 treatment had a more pronounced effect on soybean leaf N content compared to P-2 treatment; leaf total P content decreased gradually from branching to flowering stages, and then declined post the flowering stage. The highest leaf P content was found in high-rate P fertilizer treatment which is significantly higher than the non-P-fertilizer control; soybean leaf K content increased gradually from branching to flowering stages and it started to decline post the flowering stage. Plants receiving P fertilizer treatment also had higher K contents compared to control; but there were no big differences among between different levels of P fertilizers. These results indicate that appropriate use of P fertilizer helps to improve leaf K nutrient status.

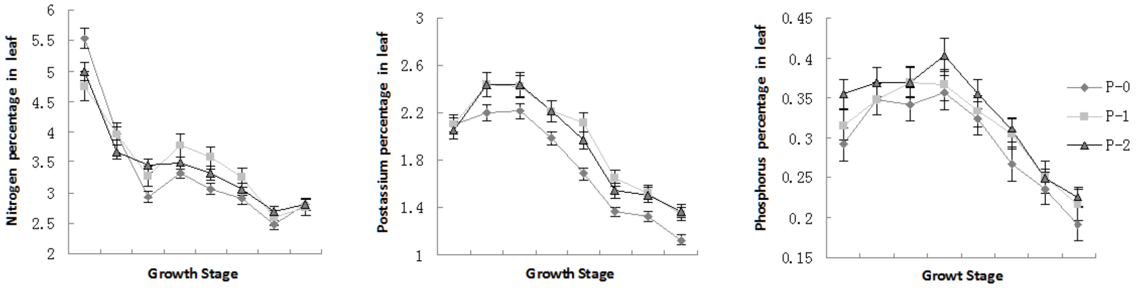

Figure 2.*Variation of total N, P, K content in soybean canopy at different growth stages*

Simulation models for soybean leaf total N, P, K contents

In this study, the original data of canopy spectral reflectance and those transformed by the function of reciprocal, derivative and algorithm, were used to identify the optimal band regions that would produce a good correlation between canopy spectral data and leaf total N, P, K contents, and to establish simulation models of these three mineral nutrients. Results indicate the correlation efficient (r) of the simulation equations depends on data transformation *(Table 2)*. The correlation efficient of the four transformed datasets was at an extremely significant level ($p<0.01$) but from different bands for total N, P and K. The first and second-derivatives of the spectral reflectance had a better correlation with N, P, and K than the other three transformed datasets. These results indicate that the first and second derivatives may be able to eliminate side-effects from soil, the depth of leaf color, and other environmental factors. Thus they are correlated with physiological-chemical properties of chlorophyll and other growth factors (Malthus et al., 1991).

Table 2. *Correlation between soybean leaf essential mineral nutrients and transformed spectral data (N=144)*

Spectral data	Leaf total N (%)		Leaf total P (%)		Leaf total K (%)	
	Bands	Correlation coefficient	Bands	Correlation coefficient	Bands	Correlation coefficient
ρ	569nm	0.5116**	771nm	0.3749**	777nm	0.3749**
1/ρ	566nm	-0.3967**	768nm	-0.4092**	566nm	-0.3967**
Log(ρ)	567nm	0.4798**	769nm	0.3939**	992nm	0.3925**
ρ′	625nm	-0.7720**	909nm	-0.5960**	908nm	-0.5631**
(1/ρ)′	553nm	-0.5203**	870nm	0.5569**	798nm	0.4233**

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Log(ρ) ′	592nm	-0.7003**	909nm	-0.6172**	592nm	-0.5447**
ρ″	423nm	-0.7829**	806nm	-0.5473**	432nm	-0.5398**
(1/ρ)″	519nm	-0.5279**	910nm	-0.5536**	539nm	0.4756**
Log(ρ) ″	423nm	-0.7138**	680nm	-0.5894**	539nm	-0.5461**

Note:** indicates an extremely significant correlation (P< 0.01), * indicates a significant correlation (P< 0.05).

It was shown that soybean leaf total N content has the best and positive correlation with the second-derivative (ρ″) of the spectral reflectance at the 423 nm band (*Table 2*); the simulation equation is: y=-19.153x+3.1114 (r=-0.7829, p<0.01; RE=0.1713); the measured and analog value predicted from the model is r=0.7908 (p<0.01) (*Fig. 3*). The simulation equation was constructed for the total P content and Log(ρ) ′ of the first-derivative of spectral reflectance at 909 nm as: y=-0.2939x+0.5889 (r=-0.6172, p<0.01; RE=0.2428); The measured and simulated values were significantly correlated (r=0.7386, p<0.01) (*Fig. 4*). To determine the optimal correlation coefficient between soybean leaf total K content and the first derivative of spectral reflectance at 908 nm, a function model was constructed using the derivative data and leaf total K content and it is written as: y=-0.4157x+1.874(r=-0.5631, p<0.01; RE=0.1345) and there was a significant correlation between the measured data and the analog values predicted using the model (r=0.6421 (p<0.01) (*Fig. 5*).

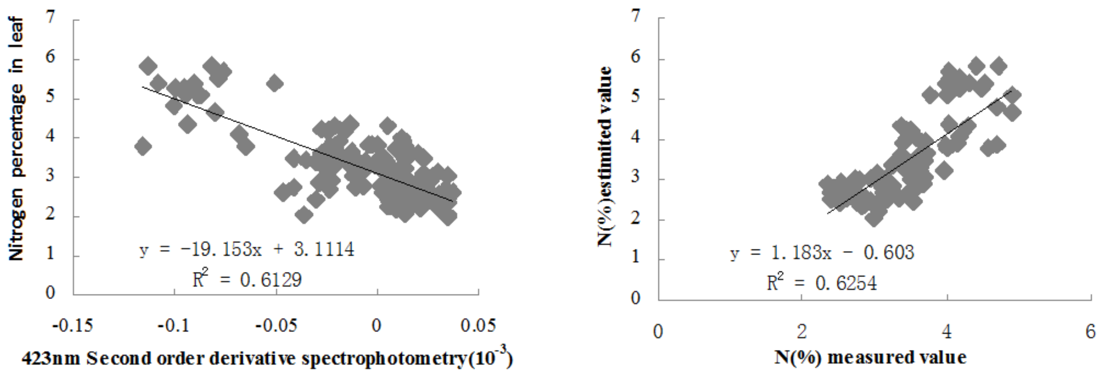

Figure 3. *Correlation analysis between total leaf nitrogen content and optimal transformation of the reflectance spectrum of soybean canopy (N=144)*

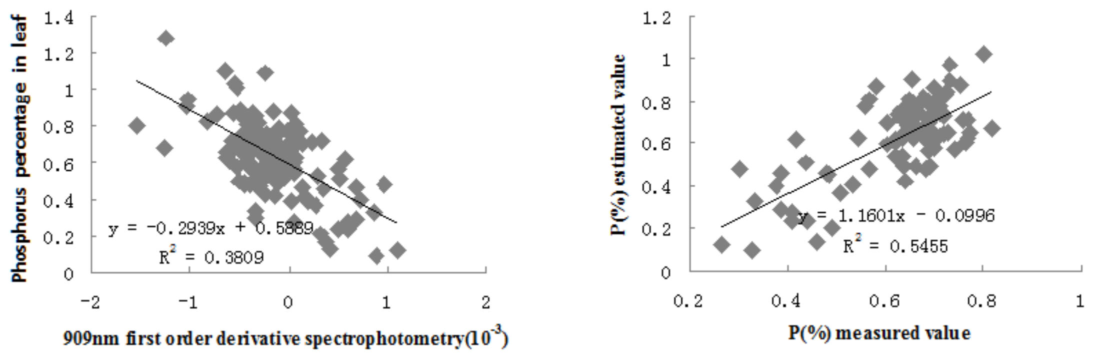

Figure 4. *Correlation analysis between the simulated and the measured total phosphorus content of soybean leaves (N=90)*

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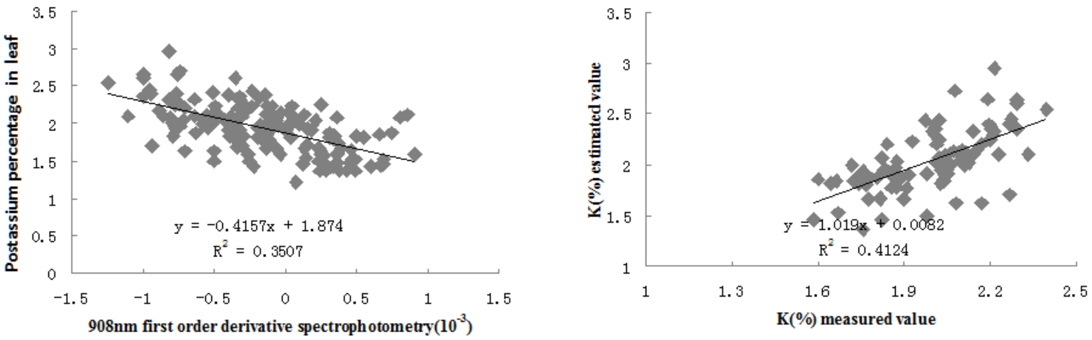

Figure 5. *Correlation analysis between total leaf potassium content and the derivative spectra (N=144) in soybean canopy*

Correlation between red edge parameters and soybean leaf N, P, K contents

Results of the correlation analysis between the red edge parameters including red edge position (λ_{red}), red edge slope ($D\lambda_{red}$) and red edge area (S_{red}) and leaf total N, P, K were contained in *Table 3*. Among the simulation models, the fit equation for red edge area (S_{red}) and soybean leaf total N content is: y=3. 1714x+1.7001(r=0.4676, p<0.01; RE=0.2439). The correlation coefficient between measured and analog values from simulation is: r=0.7088 (p<0.01) (*Fig. 6*). The simulation equation for the red edge slope ($D\lambda_{red}$) and total P content is: y=20.204x+0.3811(r=0.3981, p<0.01; RE=0.2739); the correlation coefficient between the measured and analog values is r=0.5918 (p<0.01) (*Fig. 7*). The simulation equation for the red edge area (S_{red}) and leaf total K is: y=1.009x+1.589 (r=0.4121, p<0.01; RE=0.1506); The correlation coefficient between measured and analog values is r=0.5791 (p<0.01) (*Fig. 8*). These results indicate that red edge area (S_{red}) and the slope ($D\lambda_{red}$) and the position (λ_{red}) each have lower correlation with leaf total N, P and K contents. Therefore these red edge parameters are not suitable for the purpose of predicting leaf total N, P, K contents under the experimental conditions.

Table 3. *Correlation between soybean canopy red edge parameters and leaf nutrient contents*

Red edge parameters	Leaf total N (%)	Leaf total P (%)	Leaf total K (%)
Red edge position λred	0.2582**	0.0964	0.0964
Red edge slope Dλred	0.4590**	0.3981**	0.3608**
Red edge area Sred	0.4674**	0.3641**	0.4120**

Note:** indicates an extremely significant correlation (P< 0.01), * indicates a significant correlation (P< 0.05), (N=144).

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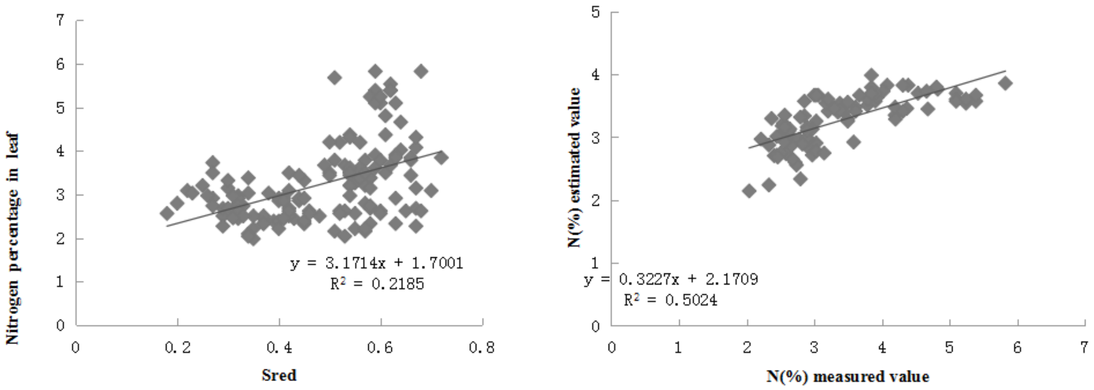

Figure 6. *Correlation analysis between the simulated total nitrogen content and the red edge parameters (N=144)*

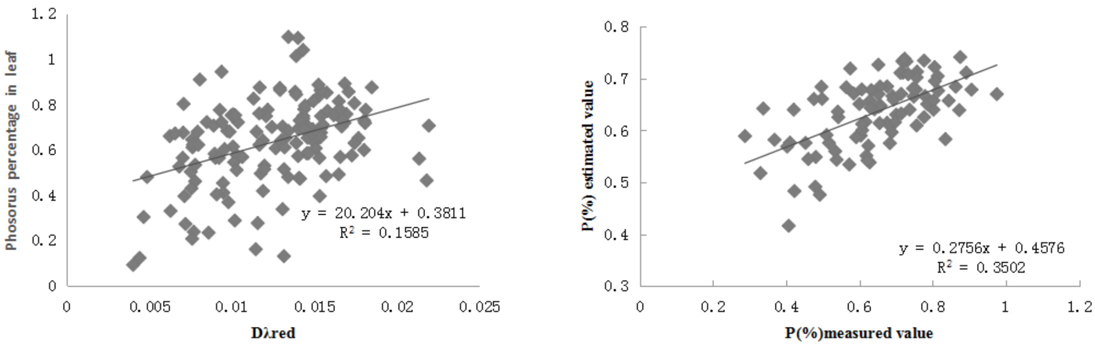

Figure 7. *Correlation analysis between the total leaf phosphorus contents and Dλred and Sred (N=144) of soybean canopy*

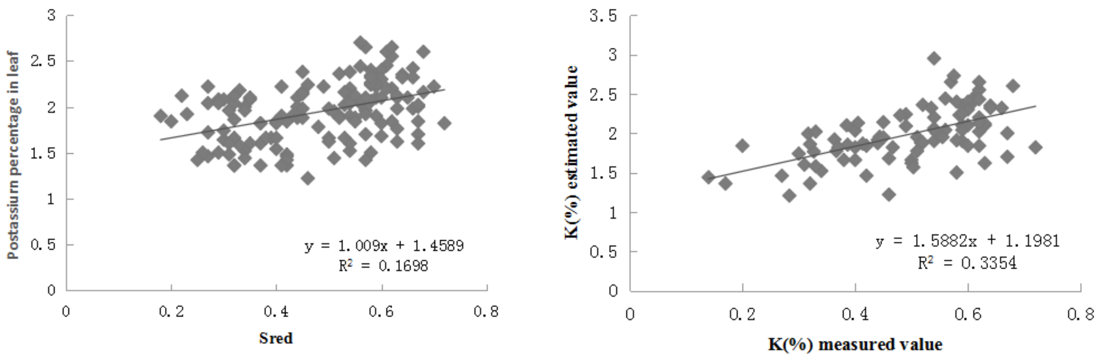

Figure 8. *Correlation analysis between the simulated and measured total potassium content of soybean leaves (N=90)*

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Vegetation index simulation model

Data of spectral reflectance from a selection of optimal bands were used to construct simulation models for vegetation indices and leaf total N, P and P content. The four generally used vegetation indices, DVI, RVI, NDVI and RDVI, were calculated to select the optimal spectral bands (*Table 4*), and then soybean LAI simulation model were constructed for these growth parameters. After simulation test, the equations giving the best correlation coefficient (r) and smallest average relative error (RE) was selected as the optimal simulation model.

Table 4. *Soybean leaf mineral nutrients and vegetation index simulation model analysis (N=144)*

	Vegetation index	Spectral band regions (nm)		The fitted equation	Correlation coefficient	Average relative error (RE)
Total leaf N content (%)	DVI	762	743	y=22.006x+2.0303	0.6242**	0.1195
	RVI	762	743	y =13.044x-11.343	0.5559**	0.1271
	NDVI	762	743	y =29.693x+1.5944	0.5576**	0.1269
	RDVI	762	743	y = 26.604x+1.7856	0.6152**	0.1192
Leaf total P (%)	DVI	771	757	y=16.62x+0.2946	0.5750**	0.2292
	RVI	911	756	y =13.044x-11.343	-0.3887**	0.2709
	NDVI	762	693	y =29.693x+1.5944	0.4207**	0.2667
	RDVI	771	757	y = 15.709x+0.3168	0.4656**	0.2466
Leaf total K content (% in dry weight)	DVI	762	734	y=3.2464x+1.5448	0.4755**	0.1468
	RVI	762	742	y =3.3287x-1.82	0.4207**	0.1534
	NDVI	761	735	y =4.2976x+1.4181	0.4591**	0.1471
	RDVI	762	722	y = 2.3962x+1.2782	0.5318**	0.1402

Note:** indicates an extremely significant correlation (P< 0.01), * indicates a significant correlation (P< 0.05); x is vegetation index

The simulation equation for leaf N content was constructed using the difference vegetation index (DVI) [762,743]. It is described as: y=22.006x+2.0303(r=0.6242, p<0.01; RE=0.1195). The measured data and simulated analog values have a significant correlation (r=0.7678, p<0.01) (*Fig. 9*). The simulation equation for DVI [771,757] and leaf total P is written as: y=16.62x+0.2946(r=0.5750, p<0.01; RE=0.2292), with a significant r (r=0.7572, p<0.01) between the predicted analog values and the measured data (*Fig.10*). The simulation equation using the normalized difference vegetation index (NDVI) [762,722] is: y = 2.3962x+1.2782(r=0.5318, p<0.01; RE=0. 1402). The measured data and simulated analog value has a significant correlation (r=0.6303, p<0.01) (*Fig. 11*).

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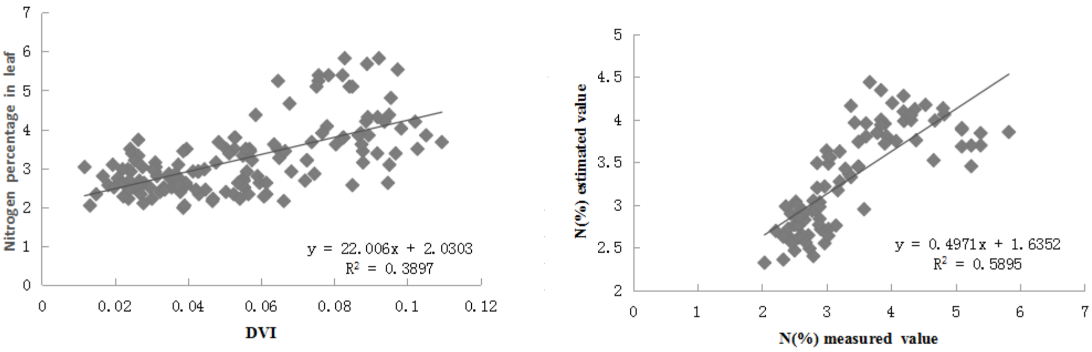

Figure 9. *Correlation analysis between total leaf nitrogen contents and vegetation index of soybean canopy*

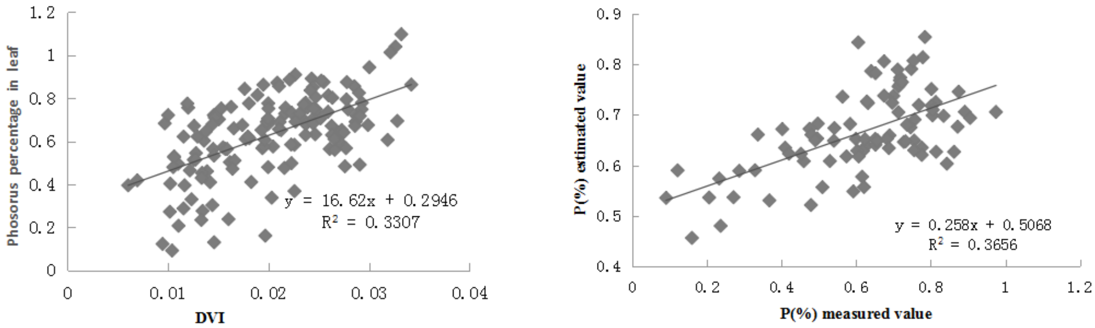

Figure 10. *Correlation analysis between total leaf phosphorus content and vegetation index of soybean canopy*

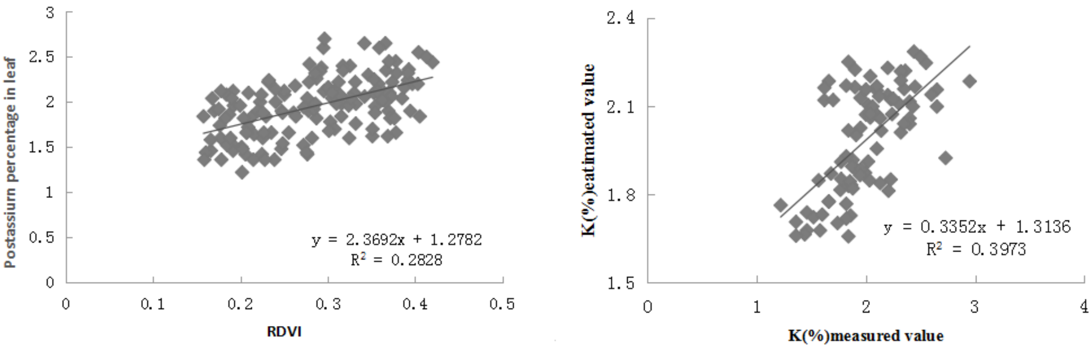

Figure 11. *Correlation analysis between total leaf potassium content and vegetation index of soybean canopy*

Conclusion and discussion

The following conclusions have been *drawn* from this study:

- *Models for hyperspectral simulation* of major mineral nutrient contents (leaf total N, total P, total K) were constructed using the original data and those *transformed* by the *reciprocal* function, logarithm, derivative, of *spectral*

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reflectance, *the* red edge parameters, and the four vegetation indices *of soybean canopy. It was* found that the first derivative and the second *derivative of spectral reflectance* at 423nm *can reliably predicate leaf total N content using the* following equation: y=-19.153x+3.1114 (r=-0.7829 RE=0.17130). The predicted data using this modes is well- correlated value (r=0.7908**) with measured data, thus the model has competitively high predictive power.

- Among model equations developed using the l*ogarithmic spectrum* data, the first *and* the second *derivatives and* DVI were able to predict leaf total P content at a degree of high accuracy. At the 909nm wavelength, *the equation for* the first *derivative of logarithmic spectrum is:* y=-0.2939x+0.5889(r=-0.6172 RE=0.2428),which produces a significant correlation coefficient (r=0.7386**, p<0.01),between measured and analog values and it is the best among the three models.
- The derivative- transformed and renormalized difference vegetation index (RDVI) can both accurately predict leaf total K content. At 908nm, the equation using the first derivatives of spectral data is: y=-0.4157x+1.874 (r=-0.5631 RE=0.1345). The correlation coefficient between measured and analog values is r=0.6298**, therefore it is the most powerful equation for modeling leaf K content.
- In summary, in this study, the reflectance spectral data from soybean canopy were collected and processed to develop simulation models for leaf growth parameters and mineral nutrient contents. A wide application of these models is expected in crop management. An extremely strong correlation was found between content of major nutrients (total N, P K) and the transformed data of canopy spectral reflectance. The sensitive bands for total leaf N, P K contents are 423nm, 909nm and 908nm. Several highly accurate simulation equations were developed for these bands. But during the process of screening for the optimal band range, it was found that a large number of bands had an extremely significant correlation (p<0.01) with leaf mineral contents, furthermore, the differences between those bands were very small.
- The hyperspectral features within the visible light region (400~700nm) are sensitive to N status in the canopy of cotton (Wang and Li, 2012). The 350~730 nm and 1420~1800 nm are the wavelength ranges that are sensitive to P contents in maize plants (Wang et al., 2007). These researches consistently have demonstrated that there is no single band that can produce enough spectral data to simulate a plant growth parameter, instead, data from “a range of optimal wavelengths” have to be used to develop the spectral signatures. More studies will be conducted to establish and validate the most stable and most effective wavelengths for each of the plant growth parameters for soybean crop.

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