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Estimation of wheat chlorophyll content based on HJ satellite CCD

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Abstract: Chlorophyll content is an important indicator for assessing crop health and predicting crop yield. It is possible that chlorophyll content (CC) was quickly and non-destructively estimated by remote sensing. The objective of the experiment was to develop precision agricultural practices for predicting CC of wheat. In this study, we compared some spectral parameters (SPs) and CC with the determination coefficient (R^2), and combined these SPs by stepwise regression methods. The results indicated that the 1.45SIPI-1.05PSRI, the R^2 value was 0.6589 and corresponding the root mean square error (*RMSE*) was 1.463, and it can be used to improve the prediction accuracy of CC.

Introduction

Leaf chlorophyll (Chl) content provides valuable information about the physiological status of plants, and there is a need for accurate, efficient, practical methodologies to estimate this biophysical parameter. Developing methods to quantify leaf pigment content and composition from remotely sensed data provide a unique nondestructive capability to assess photosynthetic processes in plants and monitor and diagnose foliar conditions and different kinds of environmental stresses.

Recently, Chl content analysis with non-destructive remote sensing methods have been developed. There are many works which bears on the relationships between Chl content and Spectral parameters [1-7], and many papers have created new indexes which are well-correlated with Chl [8-13]. These new methods have been applied extensively for non-desructive estimation of leaf Chl content in the field crop management. Curran et al. (1990) explored the relationship between reflectance red edge and chlorophyll content in slash pine [8], Buschmann and Nagel (1993) have been demonstrated that between reflectance in visible range and leaf Chl content existed essentially nonlinear [1]. Gamon&Surfus (1999) reported that the relationship between normalized difference vegetation index (NDVI) and total Chl content is markedly different in the coniferous *Pseudotsuga menziesii* and the herbaceous *Helianthus annuus* [5], Carter, et al. (2001) studied the relationships between spectral characteristics and chlorophyll concentration [14]. Spectral reflectance methods were used to estimate Chl content by Gitelson et al. (2001,2002) [6-7], Le Maire et al. (2004) have found that the reflectances had strong relationships with Chl content in the green and red edge wavelengths and were usually preferred, because these relfectances were more sensitive to moderate to high chlorophyll content [15]. Carter and Knapp (2001) indicated that a quantitative estimation of chlorophyll content mainly based on spectral reflectance at 550 nm and/or around 700 nm have been tested and showed a good correlation with Chl content [14]. Gitelson et al. (2005) proved that a good correlation between ($R_{NIR}/R_{red\ egde}$)–1 and (R_{NIR}/R_{green})–1 and Chl content [16], and applied for estimating gross primary production (GPP) based on the relationship between the Chl content and GPP (Gitelson et al., 2006; Peng et al.,2011) [17,18],and estimating anthocyanins and chlorophlls in anthocyanic and grapes leaves [19,20], Zhang et al. (2010) predicted chorophyll concentration based on leaf reflectance, transmission and absorption for rice[21]. Some authors have found a stronge linear or curvilinear relationships between SPAD values and and leaves chorophyll content (LCC) [22-23], and Markwell et al. (1995) present theoretical justification for using an exponential equation to describe the relationship between LCC and the SPAD-50 meter output value[4]. However, the majority of the above cited studies are focused on the single spectral parameter at growth stage in crops, few studies have been performed on combining different spectral parameters was used to estimate Chl content for wheat. The objectives of the present work were to analyze the relationships between the spectral parameters and combining spectral parameters and Chl content, to determine the best-fit determination coefficient (R^2) values for the relationships of the Chl content to the spectral parameters, and to establish reliable regression equations for improving the prediction accuracy of Chl content in wheat.

Materials and Methods

Study area

Field measurements were carried out across 2010 and 2011 in jiangsu province,China (Fig. 1), with a typical continental coastal climate. The sudty sites are located at latitude 30°45′-35°20′, longitude 116°18′-121°57′, the total area of one thousands and twenty-six square kilometers. Crop cultivated area are four millions and ninty thousands ha, the main crop are regional climate: the maximum temperature was 26-28.8˚C in summer, the minimum temperature was -1-3.3˚C in winter, the average annual temperature is 15.5˚C, temperature changes slowly in all season, the temperature difference between day and night is smaller. The annual precipitation averages 150-400 mm and evaporation averages is 855 mm, sunshine time are 1816-2503 hours [24].

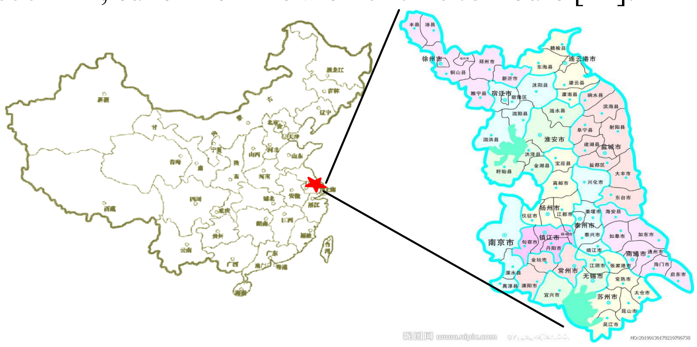

Fig.1. Location of the research region

HJ-1 satellite data

HJ-1 satellite system named China's environmental disaster satellite, two of the optical satellites, HJ-1A and HJ-1B,were launched on September 6,2008. HJ-1A carries a Wide Field Charge-coupled Device (CCD) camera and a Hyperspectral Imager. HJ-1B satellite carries the same CCD camera and an IR camera. The CCD cameras collect information from four bands (0.43-0.52 μ m, 0.52-0.60 μ m, 0.63-0.69 μ m, and 0.76-0.90 μ m) with 30 m resolution and a 720 km swath. The infrared scanner collects information from four IR bands (0.75-1.10 μ m, 1.55-1.75 μ m, 3.50–3.90 μ m, and 10.5-12.5 μ m) with 150-300 m resolution and a 720 km swath. The hyperspectral imager, China’s first such satellite, collects information at 110 bands (5 nm radio) with a 100 m spatial resolution and a 50 km swath. The launch of these satellites and use of their sensors for disaster mitigation, planning, and response will greatly improve China’s future disaster management practices and policy making.

Remote sensing data processing

This studies using the HJ-1 image data at the secondary level in 2010 and 2011 from March to May, track number is 76. All HJ-1 satellite image data were registrated by using the ENVI4.7 remote sensing image processing software.Ground control points (GCPs) located using Differential GPS on the course of field survey. The HJ satellite image data were completely corrected by using the ENVI module. Map projection used geographic (Lat/Lon) as projection type WGS84, pixel size 30 m×30 m. Radiation calibration, converting raw digital numbers (DN) into top of atmosphere reflectance according to Eq.(1):

$$\rho=(DN/C0 + M0)\times\cos\theta \quad (1)$$

Where ρ and C0 are normalized reflectance and the absolute calibration coefficient of gain, M0 is offset, θ is the sun elevation angle.

Plant measurement

The chlorophyll meter (SPAD-502 Minolta Camera Co. Ltd., Japan) has been developed to estimate the Chl status of crops. Sampled time and transited time of satellite images were synchronization. The leaves Chl content measured thirty representative wheat leaves samples by using SPAD and then to average.

Statistical analysis

The correlations between chlorophyll content data and spectral parameters indices were analyzed using SPSS software (16.0,SPSS,Chicago,IBM,USA). Coefficient of determination (R^2) and root mean square error (*RMSE*) were used as metrics for quantifying the amount of variations explained by the relationships developed and their accuracy. Generally, the performance of the model was estimated by comparing the different coefficient of determination (R^2) and root meat square error (*RMSE*) in prediction. The higher the R^2 and the lower the *RMSE*, the higher the precision and accuracy of a model to predict crop chlorophyll content.

Results and Discussion

Spectral parameters selection

Ten spectral parameters (SPs) were selected according to the literature, and it showed a significant relationships between SPs and cchlorophyll content (CC) (Table 1). establishing canopy CC estimation model for wheat through further studies of the correlation between these parameters and CC. To find SPs was sensitive to CC, we studied the correlations between SPs and CC (Table 2).

The correlations between SPs and CC in the different growth stages indicated that the anthesis was stronger than others (Table 2). This results was in agrrement with Eitel et al. (2008), who used simulated data for wheat[25]. The best retionships between SPs and CC were SIPI, GNDVI, SIPI, SIPI and PSRI at tillering, jointing, heading, anthesis and filling, respectviely. The SIPI and GNDVI have positively significant correlated with CC at tillering and jionting, and the correlation coefficient (*r*) were 0.622 and 0.630, the SIPI and PSRI were negatively correlated at heading, anthesis and filling, the *r*-value of -0.627, -0.729 and -0.630, respectviely. The results indicated that the best SPs was SIPI, can be used to estimate CC at anthesisi for winter wheat, and SIPI regression model were feasible for predicting CC, suggesting that SIPI, GNDVI and PSRI were used to estimate CC at different growth stages.

stepwise regression methods

To establish a new index regression model, we combined B1, B3, B4, GNDVI, SIPI and PSRI by stepwise regression methods at anthesis. Firstly, compared with six spectral parameters account for weight to predict CC, and the best remaining variable was added. Secondly, all variables currently in the regression were checked to see if any can be removed, using the greater than 10% significance criterion. The process continues until no more variables were added or removed. Finally, we got the new index was 1.45SIPI-1.05PSRI and used for estimating CC and R^2 was 0.6589 (Fig. 2). To validate this model accuracy, we compared predicted value with actual value,

Table 1. Summary of selected SPs,wavebands,citations for CC.

Spectral parameters	Abbreviation	Algorithm	Source
	B1	the first band of HJ satellite	In this paper
	B2	the second band of HJ satellite	In this paper
	B3	the third band of HJ satellite	In this paper
	B4	the fourth band of HJ satellite	In this paper
normalized difference vegetation index	NDVI	(B4-B3)/(B4+B3)	Gitelson et al., (1996)
Optimal soil adjusted vegetation index	OSAVI	1.16×(B4-B3)/(B4+B3+0.16)	Rondeaux et al., (1996)
Green normalized difference vegetation index	GNDVI	(B4-B2)/(B4+B2)	Daughtry et al., (2000)
Structureintensive pigment index	SIPI	(B4-B1)/(B4+B1)	Penuelas et al., (1995)
Plant senescence reflectance index	PSRI	(B3-B1)/B4	Sims and Gamon, (2002)
Ratio vegetation index	RVI	B4/B3	Jacobsen et al., (1998)

Table 2. The correlation coefficient (*r*) between CC and the SPs at the different growth stages (n=30)

	tillering	jointing	heading	anthesis	filling
B1	-0.524**	0.260	0.438*	0.580**	0.274
B2	0.184	-0.475**	-0.219	-0.479**	-0.186
B3	-0.183	-0.399*	-0.217	-0.498**	-0.177
B4	0.313	-0.268	-0.431*	-0.489**	0.063
NDVI	0.177	0.111	-0.302	0.480**	0.193
OSAVI	0.178	0.111	-0.302	0.480**	0.193
GNDVI	0.293	0.630**	0.167	0.671**	0.180
SIPI	0.622**	-0.288	-0.627**	-0.729**	-0.198
PSRI	-0.467*	-0.207	-0.607**	-0.702**	-0.630**
RVI	0.281	0.110	-0.203	0.484**	0.168

Note: n=number of pairs of data. “*” and “**” Model significant at the 0.05 and 0.01 level of probability, respectively.

the results showed that the *RMSE* was 1.463 (Fig. 2). The results demonstrated that the index of 1.45SIPI-1.05PSRI can be used to improve the prediction accuracy of CC. The new index of 1.45SIPI-1.05PSRI gained by stepwise regression methods (Fig. 2), and it was better to predict CC than six SPs alone. This ability was mainly due to the combind indexes was not only more sensitive to CC, but also less negatively influenced by variations in LAI and soil background reflectance.

Wheat CC distribution

The results showed that the wheat average CC distribution at anthesis in 2010 and 2011 (Fig. 3). The lowest and highest SPAD were 43-49 and 64-70, accounted for 28 % and 18%, respectively. The SPAD value were 50-56 and 57-63 accounted for 34 % and 20%, respectviely. SPAD trends and status were consistent with the wheat growth stages.

Conclusion

According to previous studies, the chlorophyll content (CC) was predicted by using the spectral parameters and stepwise regression methods, the main results and conclutions were following. we

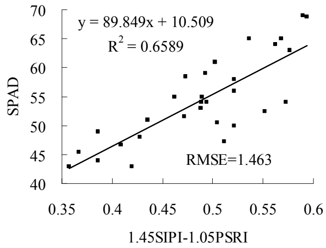

Fig.2. Quantitative relationships of the CC to 1.45SIPI-1.05PSRI, in wheat.(n=30)

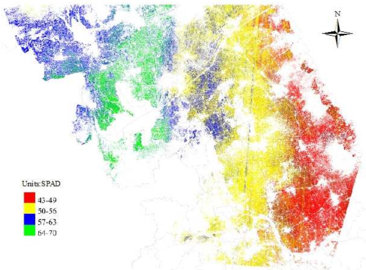

Fig.3. Distribution of average CC at anthesis,2010 and 2011.

combined B1, B3, B4, GNDVI, SIPI and PSRI by stepwise regression methods at anthesis and got the new index was 1.45SIPI-1.05PSRI, R^2 and *RMSE* were 0.6589 and 1.463, respectively.

These results indicated that different SPs were collected to estimate CC at anthesis, and these spectral parameters (SPs) combined to improve the prediction of CC by stepwise regression methods. This method lead to a new idea to predict accurately CC by combining different SPs, and improving single SPs defection to reduce some factors affected. More research is needed in order to test the predictive power of the proposed indices. New methodologies could also provide enhanced estimates of CC.

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