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Article

Evaluating Multispectral and Hyperspectral Satellite Remote Sensing Data for Estimating Winter Wheat Growth Parameters at Regional Scale in the North China Plain

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Summary: Timely monitoring of crop growth status at large scale is crucial for improving regional crop management decisions. The main objective of the recent study is a model development to predict and estimate crop parameters, here biomass, plant N concentration and plant height, based on multi- and hyperspectral satellite data. In this contribution, the focus is on relating orbital multispectral (EO-1 ALI) and hyperspectral (EO-1 Hyperion) measurements to winter wheat parameters for regional level applications. The study was conducted in Huimin County, Shandong Province of China in the growing season of 2005/2006 involving three big winter wheat fields managed by different farmers. Winter wheat growth parameters including aboveground biomass, plant N concentration and plant height were collected at different growth stages. Three different predicting models were investigated: traditional vegetation indices calculated from broad and narrow bands, and Normalized Ratio Indices (NRI) calculated from all possible two-band combinations of Hyperion between 400 and 2,500 nm. The results indicated that TVI performed best among the tested vegetation indices using either broad (R2=0.69, 0.32 and 0.64 for biomass, N concentration and plant height, respectively) or narrow (R2=0.71, 0.33 and 0.65 for biomass, N concentration and plant height, respectively) bands. The best performing Normalized Ratio Index (NRI) selected through band combination analysis were significantly better than TVI, achieving R2 of 0.83, 0.81 and 0.79 for biomass, plant N concentration and plant height, respectively. The different NRI models use wavebands from the near infrared (NIR) (centered at 874, 732, and 763 nm) and short wave infrared (SWIR) (centered at 1,225 and 1,305 nm) spectrum with varying bandwidth be-

Zusammenfassung: *Anwendung Multispektraler- und Hyperspektraler Fernerkundung zur Ableitung von Bestandsparametern des Winterweizens in der Nordchinesischen Tiefebene.* Methoden und Techniken der Fernerkundung fungieren als ein wichtiges Hilfsmittel im regionalen Umweltmanagement. Ziel der vorliegenden Studie liegt dabei auf der Modelentwicklung zur Ableitung von Pflanzenparametern für Winterweizen aus multispektralen (EO-1 ALI) und hyperspektralen (EO-1 Hyperion) Bestandsmessungen. Hierfür wurde ein Feldversuch in der Nordchinesischen Tiefebene durchgeführt, wobei Pflanzenparameter zu verschiedenen Wachstumsstadien aufgenommen wurden. Um die aufgenommen Parameter mit den Fernerkundungsdaten in Beziehung zu setzen, wurden drei verschiedene Modelvarianten untersucht: traditionelle Vegetationsindices berechnet aus Multispektraldaten, traditionelle Vegetationsindices berechnet aus Hyperspektraldaten sowie die Berechnung von Normalized Ratio Indices (NRI) basierend auf allen möglichen 2-Band Kombinationen im Spektralbereich zwischen 400 und 2.500 nm.

Für traditionelle Vegetationsindices (SR, NDVI und SAVI), berechnet aus Multispektral- sowie aus Hyperspektraldaten, wurden geringe statistische Beziehungen zu Pflanzenparametern erzielt. Neben den Standardspektralbereichen (grün, rot, nahes Infrarot) bietet die hohe spektrale Auflösung des Hyperion Sensors jedoch die Möglichkeit, weitere Spektralbereiche mit Pflanzenparametern in Beziehung zu setzen. Aus der Untersuchung aller möglicher 2-Band Kombinationen konnten starke Korrelationen zwischen Pflanzenparametern und Fernerkundungsdaten bei der Kombination von Bändern aus dem nahen Infrarot (NIR) mit Bändern aus dem kurwelligen Infrarot (SWIR) festgestellt werden.

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tween 10 and 190 nm. The result of this study suggest that vegetation indices derived from NIR- and SWIR-Hyperion spectrum are better predictors of plant aboveground biomass, nitrogen concentration and plant height than indices derived from only visible spectrum. More studies are needed to further evaluate the results using data from more diverse conditions.

Für die Pflanzenparameter Biomasse, Pflanzenstickstoffgehalt und Pflanzenhöhe wurden Korrelationen (R2) von 0,83, 0,81 und 0,79 erzielt. Das Ergebnis der Studie zeigt, dass sich Anwendungsoptimierte Vegetationsindices, berechnet aus schmalen hyperspektralen Bändern des RE, NIR und SWIR, zur Ableitung von Pflanzenparametern eignen und gegenüber Standard Vegetationsindices deutlich bessere Ergebnisse liefern können.

1 Introduction

Timely monitoring of crop growth status is important for dynamic in-season site specific crop management, detection of plant vitality, assessment of seasonal production as well as environmental pollution control and yield prediction (Miao et al. 2009, Laudien & Bareth 2006, Zhao et al. 2004, Hansen & Schjoering 2003). Traditional techniques for the measurement of accurate crop parameters such as plant aboveground biomass and nitrogen concentration are destructive, extremely cost and labour intensive and not able to provide spatial distributed data on regional level (Lu 2006). The estimation of these parameters can be done more efficiently by non-destructive spectral reflectance observations (Daughtry et al. 2000), obtained from field-, airborne- or satellite based sensors. For the linkage of crop parameters with spectral reflectance measurements, a wide range of vegetation indices were developed (Zhao et al. 2004, Haboundane et al. 2004, Broge & Mortensen 2002). Vegetation indices obtained from spectral reflectance measurements are designed to enhance the vegetation cover signal while minimizing the response of various background materials (Schowengerdt 2007). They are mainly based on the difference between low reflection due to strong absorptions by foliar pigments in the red spectrum and high reflection of structural components (cell walls) in the near infrared spectrum (Kumar et al. 2003, Lillesand et al. 2004). In the past decades, many attempts have been made to estimate crop parameters at regional level, either directly from remote sensing data or by assimilating remote sensing data into crop models (Schneider 2003). A lot of earth observation satellites carrying multispectral imaging sensors are available (Wooster 2007), providing data that can be used for the calculation of broad band vegetation indices (Lu 2006). Vegetation indices calculated from the visible and near infrared bands of multispectral scanners have been used to estimate crop parameters such as standing biomass and grain yield (Tucker 1979, Thenkabail et al. 1995, Singh et al. 2002, Doralswamy et al. 2003), leaf area index (LAI) (Cloutis et al. 1999) and plant nitrogen content (Reyniers & Vrindts 2004). At higher vegetation densities, standard broadband vegetation indices, such as Simple Ratio (SR) or Normalized Difference Vegetation Index (NDVI) are generally less accurate (Jongschaap & Schouten 2005) and tend to saturate (Haboudane et al. 2004, Mutanga & Skidmore 2004), which results in a limited prediction value of crop parameters when LAI exceeds two (Haboudane et al. 2004). Improvements could be achieved by using hyperspectral radiometers, which can acquire a continuous electromagnetic spectrum for each pixel between 350 and 2,500 nm (Hansen & Schjoering 2003). The sensitivity of hyperspectral vegetation indices for estimation of crop parameters has already been demonstrated with significant improvements compared to broad bands by several authors during the past several decades (Sinclair 1971, Fillela et al. 1995, Strachan et al. 2002). Beyond narrow band standard vegetation indices, imaging spectroscopy provides the opportunity of using more adequate wavebands or waveband combinations to estimate biophysical parameters (Ceccato et al. 2002). According to this, different approaches for index calculation based on all waveband combinations were developed and successfully used for estimation of wheat grain yield (Xavier et al.

2006), wheat biomass and Nitrogen content (Hansen & Schjoering 2003, Thenkabail et al. 2000) as well as land cover classification (Thenkabail et al. 2004). Also, Ferwerda et al. (2005) used waveband selection method successfully for the estimation of leaf nitrogen content across different species. Mutanga & Skidmore (2004) reported that waveband combinations different from the standard NDVI could overcome saturation effects of biomass estimation at full canopy cover.

A lot of studies have been conducted on improving the performance of hyperspectral vegetation indices both on excised leafs and in situ measurements, but there are only a few studies dealing with hyperspectral imaging on regional level (e. g. Smith et al. 2003, Galvaõ et al. 2005, Datt et al. 2003). By using high spectral resolution space born radiometers (e. g. Hyperion sensor on Earth Observation-1 satellite), detailed variation in the electromagnetic spectrum between 400 and 2,500 nm can be measured over a wide area (Broge & Leblanc 2000), making this approach more efficient for large scale precision crop management.

The objective of this study was to analyse, compare and evaluate satellite based multispectral and hyperspectral images in terms of broad band and narrow band vegetation indices for the estimation of winter wheat aboveground biomass, plant N concentration and plant height. For this research interest, the optical sensors Hyperion and ALI, mounted on Earth Observation-1 satellite were selected, because they can provide multispectral and hyperspectral data simultaneously. Three different types of vegetation indices were calculated to estimate crop parameters: (1) standard broad band vegetation indices derived from multispectral sensor ALI; (2) standard narrow band vegetation indices derived from Hyperion; and, (3) systematic identification of best waveband combinations in the Hyperion reflectance spectrum from 400 to 2,500 nm using Normalized Ratio Indices (NRI) following (Thenkabail et al. 2000) and (Sims & Gamon 2002).

2 Material and Methods

Study Area

The research was accomplished in the North China Plain during the winter wheat growing season of 2006. The test fields were located in Huimin County (37.3° latitude, 117.4° longitude), Shandong Province. This area is characterized by a continental climate with precipitation maxima between June and September, typical for the warm-temperature subhumid continental monsoon climate. The average temperature is 12.3 °C and annual average precipitation sums up to 580 mm. The dominant crop rotation, up to 66 % of the cultivated area, is winter wheat followed by maize enabling two harvests per year. Huimin County was chosen because of the existence of long term field experiments managed by the Dept. of Plant Nutrition (CAU) and availability of collecting ground truth data from selected fields. Three big fields, each of which is about 5 ha and managed by different farmers, were selected for collecting ground truth information. The fields are located in the villages of Xili, Xujia, and Shizhang in Huimin County. Winter wheat in the three villages was sowed from September 17th to October 26th, 2005 and harvested in the beginning of June, 2006. All the fields were managed by the farmers according to their common practices.

Hyperion and ALI Image Data

Three Hyperion and ALI images were acquired on April 19, May 6 and May 31, 2006. The optical sensors Hyperion and ALI are mounted on the Earth Observing One (EO-1) Satellite that follows the World Reference System-2 (WRS-2) with a 16 day repeat cycle for nadir mode. Both sensors are push broom imaging spectrometers that are capable of cross-track pointing (Earth Observation-1, 2003). The multispectral Advanced Land Imager (ALI) acquires information in nine discrete bands with a spatial resolution of 30 m. An additional panchromatic channel has a resolution of 10 m. The Hyperion hyperspectral sensor collects continuous data with a VNIR and a SWIR spectrometer in the 400–2,400 nm wavelength domain. Each frame taken captures images in a 7.7 km wide and 42 km (resp.

185 km) long area (Ungar et al. 2003). Similar to the multispectral ALI, Hyperion provides also a spatial resolution of 30 m. EO-1 Hyperion images are radiometric calibrated (Level 1R) and delivered in 16-bit radiance data (Pearlman et al. 2003).

Groundtruth Measurements

Winter wheat canopy spectral reflectance was measured in the field using an ASD Fieldspec©HandHeld Pro optical sensor (Analytical Spectral Devices, Inc., Boulder, CO, USA; www.asdi.com) between 10 am to 2 pm under cloudless conditions. The HandHeld Pro device measures the visible (VIS) and near infrared (NIR) spectrum with 512 channels in the 325–1,075 nm wavelength domain. In the context of this research, the inSitu spectral measurements were only used for calibrating orbital reflectance data. After field canopy spectral data collection, crop samples were collected for aboveground biomass and plant nitrogen concentration determination on four dates: April 19, April 28, May 12 and May 30, with the corresponding growth stages from shooting to ripening stage. The measurements on April 19 and May 30 matched EO-1 satellite image collection very well; however, no ground measurements could match the EO-1 data acquisition on May 6. Therefore, agronomic measurements on April 28 and May 12 had to be interpolated to coincide with EO-1 acquisition on May 6. Aboveground biomass was destructively collected by cutting the vegetation on ground level within an area of 100 cm by 30 cm. Then the samples were dried at 70 °C to constant weight. Plant nitrogen concentration was then determined by the Kjeldahl digestion method (Bremner 1960). Around 39 to 45 measurements per field were sampled.

Satellite Image Pre-processing

Satellite image pre-processing of Hyperion and ALI data included (a) a correction for sensor artifacts, (b) an atmospheric correction as well as (c) a geometric correction. The performed pre-processing steps (Lillesand et al. 2004, Khurshid et al. 2006) were aimed to improve the quality of the images for multitemporal data analysis. For correction of sensor artifacts, uncalibrated and corrupted Hyperion bands were eliminated by applying the Flag-Mask that was delivered with the data product. A Flag-Mask indicates detectors which are unresponsive and unreliable (USGS 2007). 158 of the original 242 bands had remained for subsequent destriping (described in Datt et al. 2003). During the destriping process periodic along track stripes in image data, caused by detector errors were removed. Since some of the bands were not repairable, another 17 bands had to be excluded. The destriping and exclusion of image channels was performed with ENVI software (ITT Visual Information Solutions).

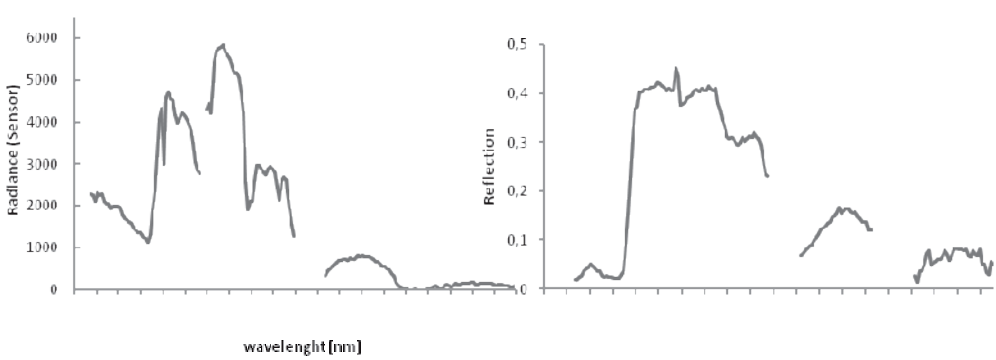

Fig. 1: Comparison of single pixel spectra before (a) and after (b) atmospheric correction. Spectra were acquired on April 19, 2006.

For some application using single satellite observations, it is of no importance to atmospherically correct image data (Schowengerdt 2007). However, in the present work, the focus was set on multi-temporal analysis as well as on matching image data to canopy spectral reflectance that was measured using a portable spectroradiometer (Fieldspec® Pro by ASD). The measured at-sensor radiance L of Hyperion and ALI data consists of reflectance from the surface and scattering from the atmosphere. Major sources of distortions of remotely sensed imagery are water vapor and aerosols (Cairns et al. 2003). To convert the Hyperion and ALI at-sensor radiance data to surface reflectance data, the MODTRAN-based radiative transfer algorithm implemented in the FLAASH module of ENVI software was used. The radiative transfer algorithm that applies for Lambertian materials, converts the at-sensor radiance L to surface reflectance ρ on a pixel-by-pixel basis as

$$\rho = \frac{L - L_a}{(\mathrm{L} - \mathrm{L_a})\, S + T_2 \frac{E_s * \cos(\theta_s)}{\pi}} \qquad (1)$$

where La is the radiance caused by atmospheric scattering; T2 is the two-way transmittance; S is the albedo of the atmosphere; θ_S is the solar zenith angle and E_S is the exoatmospheric solar irradiance. The radiative transfer algorithm is described in (Berk et al. 2000).

According to equation (1), atmospheric scattering effects were compensated and a surface reflectance spectrum for each pixel was retrieved. The comparison of single pixel at sensor radiance and surface reflectance from fully developed winter wheat is shown in Fig. 1.

The last step of the Hyperion and ALI preprocessing chain is the geometric correction, which was undertaken to rectify geometric distortions using ground control points (GPCs), sensor parameters and a digital elevation model. For orthorectification process of each scene, 25 GCPs distributed across the area of interest were selected and the image rectification was carried out by bilinear resampling method using ENVI. For evaluation purpose, other 20 independent check points were used, which resulted in overall RMSE of around 0.5 pixels (15 m) for each image.

Vegetation Index Calculation and Model Development for Crop Parameter Estimation

In this study, the reflectance spectra from multi-temporal Hyperion and ALI data were extracted on a pixel basis (cell size 30 m) on the farmers' fields in the three villages. Pixel based reflectance spectra were then used for the calculation of (1) standard broad band vegetation indices, (2) standard hyperspectral vegetation indices, and (3) narrow band Normalized Ratio Indices (NRI; Schmidt & Skidmore 2003, Sims & Gamon 2002). To compare the prediction power of broad band and narrow band crop parameter estimations, the following vegetation indices were calculated: Simple Ratio (SR), Normalized Difference Vegetation Index (NDVI), Soil Adjusted Vegetation Index (SAVI) and Triangular Vegetation Index (TVI). The SR, NDVI and SAVI vegetation indices are based on the difference between strong absorption of solar radiation in the red, caused by chlorophyll pigments and the high leaf cellular reflection in the near infrared. Unlike the Simple Ratio Index, the NDVI is normalized which reduces the effects of variable illuminations and limits the NDVI to values from -1 to 1 (Baret & Gyot 1991). The SAVI is intended to minimize influences due to soil optical properties. The included background factor L depends on vegetation density and requires information about the relationship between soil background and vegetation (Huete 1988). The TVI was developed by (Broge & Leblanc 2000) and is defined additional to red and near infrared reflectance by the magnitude in the green region. The detailed expressions and the notable references of the mentioned Vegetation Indices are provided in Tab. 1.

In addition to standard vegetation indices, a specific waveband selection method suggested by (Thenkabail et al. 2000) and (Sims & Gamon 2002) was used to determine best band combinations suitable for crop parameter estimation (see also Schmidt & Skidmore 2003). The two-band Normalized Ration Index (NRI) is defined as (Sims & Gamon 2002):

Tab. 1: Standard vegetation indices evaluated in this study.

Index	Name	Formula	References
SR	Simple Ratio	$SR = \rho_{NIR} / \rho_R$	(Baret & Guyot 1991)
NDVI	Normalized Difference Vegetation Index	$NDVI = (\rho_{NIR} - \rho_R) / (\rho_{NIR} + \rho_R)$	(Rouse et al. 1974)
SAVI	Soil adjuste Vegetation Index	$SAVI = (1 + L)(\rho_{NIR} - \rho_R) / (\rho_{NIR} + \rho_R + L)$	(Huete 1988)
TVI	Triangular Vegetation Index	$\mathrm{TVI} = 0.5*(120*(\rho_{NIR} - \rho_{Green}) - 200(\rho_{NIR} - \rho_{Green}))$	(Broge & Leblanc 2000)

$$NRI_{(\text{band1, band2})} = \frac{(\rho_{\text{band1}} - \rho_{\text{band2}})}{(\rho_{\text{band1}} + \rho_{\text{band2}})} \quad (2)$$

$$\text{band1} \geq \text{band 2}$$

where ρ_{band1} and ρ_{band2} are reflectance of Hyperion narrow bands in the wavelength range between 400 and 2,500 nm. The hyperspectral Hyperion Sensor allows the calculation of a total number of 9,870 (141*140/2) possible two-band combinations for each agronomic parameter. A linear regression between each vegetation index and crop parameter was performed.

3 Results

Variation of Crop Parameters

Due to different farmers' management practices, the investigated fields were different in terms of seeding time, plant density, and nitrogen application rates. As expected, the differences in management practices resulted in a wide range of variation in crop parameters (aboveground biomass, plant nitrogen concentration and plant height). Within-field variation of plant height and aboveground biomass at shooting stage (heading stage) ranged from 31.3 to 51 cm (70.3 to 90 cm), and from 0.28 to 0,79 kg/m^2 (0.72 to 1.55 kg/m^2), respectively. Plant nitrogen concentration varied from 17.1 to 37.42 g/kg at shooting stage and from 13.1 to 19.5 g/kg at heading stage. The decrease of plant nitrogen concentration during the vegetation period is due to dilution effect.

Relationship of Standard Vegetation Indices with Crop Parameters

The relationships of the different vegetation index types (broad band and narrow band) with the three crop parameters showed different results. Best individual R^2 values for broad band and narrow band standard vegetation indices were achieved for TVI (cf. Tab. 2). The narrow band TVI has high coefficient of determination values for aboveground biomass (R^2=0,71) and plant height (R^2=0,65), but low values for plant nitrogen concentration (R^2=0,33). NDVI generally has lower R^2 values than TVI. Narrow band vegetation indices did not improve the relationships significantly compared with broad band vegetation indices. None of the evaluated broad or narrow band vegetation indices performed well for plant nitrogen concentration, with R^2 being less than 0.35 (cf. Tab. 2).

Relationship of Narrow Band Normalized Ratio Indices (NRI) with Crop Parameters

A total number of 9,870 narrow band NRIs according to equation (2) were calculated from multi-temporal Hyperion data. Correlation matrices between each agronomic parameter and two-band vegetation indices were constructed. In each correlation matrix, the wavelengths of the two bands were plotted on the x and y axes and the classified coefficients of determination (R^2) between crop parameters and all possible two-band vegetation indices were plotted on a color scale (cf. Fig. 2).

The correlation matrices are only displayed below the diagonal because R^2 values are symmetrical. The R^2 values for aboveground biomass and plant nitrogen concentration ranged

Tab. 2: Coefficient of determination (R^2) between ALI broad band, Hyperion narrow band vegetation indices and measured agronomic parameters.

Sensor	Index	ALI Band / Hyperion wavelength			Coefficient of Determination R^2		
		Λ_1	Λ_2	Λ_3	biomass	plant N	pl. height
ALI broad band	SR	Red (4)	NIR (5)		0.35	0.25	0.41
	NDVI	Red (4)	NIR (5)		0.4	0.28	0.43
	SAVI	Red (4)	NIR (5)		0.55	0.21	0.49
	TVI	Red (4)	NIR (5)		0.69	0.32	0.64
Hyperion narrow band	SR	671	803		0.41	0.3	0.41
	NDVI	671	803		0.41	0.29	0.4
	SAVI	671	803		0.58	0.22	0.56
	TVI	671	803	549	0.71	0.33	0.65
Hyperion best waveband combinations	NRI_1	874	1225		0.83		
	NRI_2	732	1305			0.81	
	NRI_3	763	1225				0.79

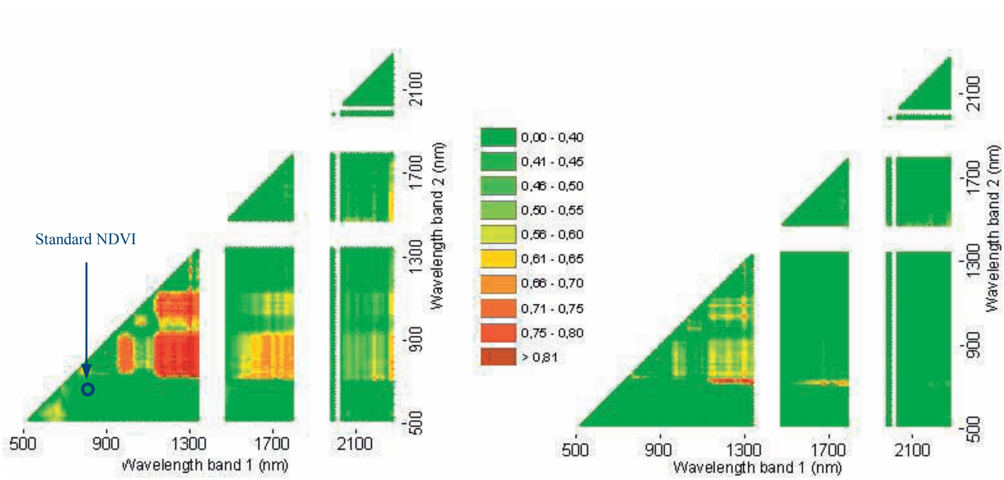

Fig. 2: Coefficient of determination (R^2) between Hyperion narrow band vegetation indices calculated from all possible two-band combinations according to equation (2) and measured agronomic parameters. (a) Biomass and (b) total nitrogen content.

from 0.08 to 0.83, and several clusters of high R^2 values could be recognized in the two matrix plots (cf. Fig. 2). Wavebands used for broadband NDVI calculation from the red and near infrared spectrum (which match red and nearinfrared ALI bands), are labeled in the matrix plot. This area shows very low correlation coefficients R^2 compared to waveband pairs forming the clusters with high correlation coefficients. Best center wavelengths of band 1 and band 2 for these patches for above-ground biomass estimation were extracted from the matrices and listed in Tab. 2. Following the same approach, best waveband pairs and bandwidth were determined for the estimation of plant nitrogen concentration (cf. Fig. 2b and Tab. 3). Similar to aboveground biomass, best waveband centers were not located in the R and NIR spectrum. The best values of NRIs for aboveground biomass, plant N concentration and plant height were 0.83, 0.81 and 0.79, respectively. The selected wavebands were centered at 874, 732 and 763 nm for band 1, and 1,225 and 1,305 nm for band 2 with bandwidth between 10 to 30 nm (cf. Tab. 2).

4 Discussion

Pre-processing of EO-1 Data

For the presented study Hyperion and ALI Level 1R data were used which are radiometrically corrected with no geometric correction applied (USGS 2007). This low level of correction assures no resampling and gives the possibility to bear a complete pre-processing chain to retrieve surface reflectance from at-sensor radiance measured with ALI multispectral and Hyperion hyperspectral sensor. Several authors (Biggar et al. 2003, Datt et al. 2003, Coops et al. 2003) pointed out the importance of correction of artefacts or atmospheric effects. A full processing chain for EO-1 Hyperion data was described by (Khurshid et al. 2006). In comparison to (Khurshid et al. 2006), the misregistration of VNIR and SWIR wavebands, which include spatial and angular shift, has been solved by a co-registration of the wavebands from the two VNIR and SWIR detectors. Due to the lack of detailed atmospheric information the atmospheric correction was performed with a standard atmosphere implemented in FLAASH (ENVI). The applied atmospheric correction resulted in a good agreement with ASD field data that were taken close to satellite overpass. Similar correction method and observed results were presented by (Datt et al. 2003) as well as by (Chen & Tian 2006).

Standard Vegetation Indices

In the first step of the study three different two-band indices (SR, NDVI, SAVI) and one three-band index (TVI) were compared in order to evaluate the capability of broad band and narrow band standard vegetation indices for crop parameter estimation. The narrow bands of Hyperion Sensor for these indices were centered at green (559 nm), red (681 nm) and near infrared (803 nm) with bandwidth of 10 nm. The corresponding ALI broadband channels were 4, 5 and 6 with a bandwidth between 40 and 80 nm.

Comparing vegetation indices based on different sources (ALI and Hyperion), only a slight improvement of hyperspectral narrow bands was observed for the three measured crop variables compared to broad band indices. Similar results were found by (Zhao et al. 2007) and (Lee et al. 2004), who tested the ability of different multispectral airborne and orbital sensor data for LAI prediction in an agricultural environment. Also Hansen & Schjoerring (2003) found a slightly improved performance of narrow bands for biomass and nitrogen status of wheat crops. On the contrary, (Broge & Mortensen 2002) and (Broge & Leblanc 2000) showed that hyperspectral vegetation indices did not perform better than their simulated multispectral counterparts. Whether broad or narrow bands were used, the standard vegetation indices had limited capability for crop parameter estimation due to canopy closure at high plant densities, which was also observed in the recent study. This saturation effect of standard vegetation indices at high canopy cover is evident for multispectral space based imaging (Tucker 1977), airborne hyperspectral imaging (Oppelt & Mauser 2004) and ground-based measurements (Mutanga & Skidmore 2004).

Narrow Band Normalized Difference Indices

In this study we evaluated the performance of these calculated band ratios that are widely used and readily adaptable in vegetation studies (Schowengerdt 2007, Gong et al. 2003, Thenkabail et al. 2000). The results in Fig. 2 show, that the two-band combinations respond in a wide range to variations in biomass. High coefficients of determination (R^2) between narrow band indices and aboveground biomass are mainly clustered in the red edge, NIR and the SWIR spectra domain. These wavebands are centered in the red edge (720 nm), the NIR peak (874 nm) as well as in the SWIR (1,225 nm and 1,750 nm) with varying spectral range between 10 and 180 nm. Similar findings for biomass estimation are summarized in (Thenkabail et al. 2004) and (Mutanga & Skidmore 2004). These spectral regions of the

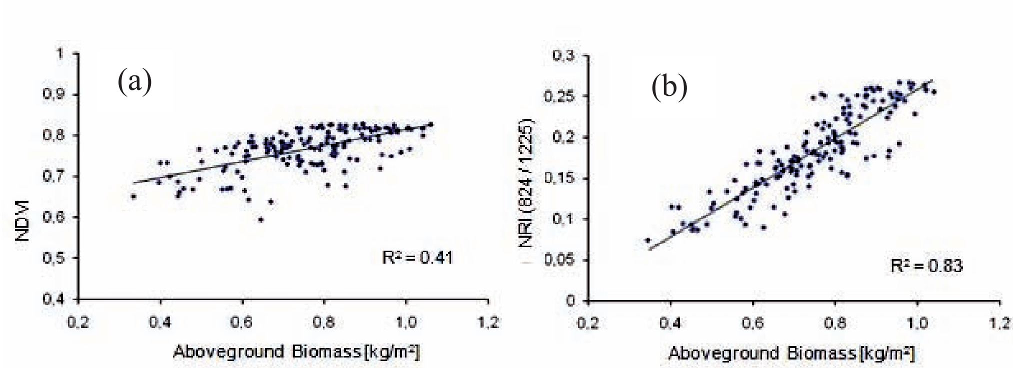

Fig. 3: Scatterplot of aboveground biomass against (a) standard narrow band NDVI (671 nm and 803 nm) and (b) best waveband combination from NRI (874 nm and1,225 nm).

NIR peak and the SWIR in the electromagnetic spectrum are among others sensitive to plant water content (Kumar et al. 2001), and consequently they have a close relationship to biomass (Hunt 1991). The best waveband combination for estimating aboveground biomass was obtained using wavebands centered at 874 nm and 1,225 nm. Similar approaches in different types of vegetation cover showed, that band combinations from the red edge (Zhao et al. 2007, Mutanga & Skidmore 2004) as well as NIR and SWIR (Mutanga & Skidmore 2004, Xavier et al. 2006) had a close relationship to LAI and aboveground biomass and performed much better than spectral bands used in standard vegetation indices.

Analog to biomass, the regression analysis between NRI and plant nitrogen concentration resulted in a wide range of R^2 values. The best correlation was achieved by combining bands from the red edge region (702 to 732 nm) with wavebands centered between 1,138 and 1,332 nm, which is in accordance to findings of (Smith et al. 2003). In addition to this, several authors showed that the VIS region had a close relationship to plant nitrogen concentration (Daughtry et al. 2000, Nguyen & Lee 2006). It is well known that canopy spectral reflectance of the VIS (400 to 700 nm) is mainly governed by foliar pigments such as chlorophyll which is induced by plant nitrogen concentration (Kumar et al. 2003, Oppelt & Mauser 2004). In addition to the VIS region some authors proved a sensitivity of red edge (LaCapra et al. 1996, Strachan et al. 2002) as well as NIR (LaCapra et al. 1996, Hansen & Schjoering 2003) for nitrogen status detection, which is coincident with the best wavebands used for NRI index calculation in our study. Furthermore, the study of (Ferwerda et al. 2005) indicated significant differences in the estimation potential of indices for nitrogen concentration across different species.

5 Conclusions

This study compared vegetation indices calculated from multispectral and hyperspectral satellite remote sensing data for estimating winter wheat aboveground biomass, plant nitrogen concentration and plant height in North China Plain, and identified better vegetation indices by systematically evaluating all possible two band combinations using Hyperion satellite hyperspectral remote sensing data from 400 to 2,500 nm. The results indicated that TVI performed best among the tested vegetation indices using either broad (R^2=0.69, 0.32 and 0.64 for biomass, N concentration and plant height, respectively) or narrow (R^2=0.71, 0.33 and 0.65 for biomass, N concentration and plant height, respectively) bands. For the evaluated standard vegetation indices, narrow band indices only had slight improvements over corresponding broad band indices. The best performing Normalized Ratio Indices (NRI) selected through band combination analysis were significantly better than TVI, achieving R^2 of 0.83, 0.81 and 0.79 for biomass, plant N concentration and plant height, respectively. They all used wavebands from the near infrared (NIR) (centered at 874, 732, and 763 nm) and short wave infrared (SWIR) (centered at 1,225 and 1,305 nm) spectrum with varying bandwidth between 10 and 190 nm. The results of this study suggest that is important to include SWIR bands in multispectral satellite sensors for agricultural crop growth status monitoring. More studies are needed to further evaluate the results using data from more diverse conditions.

We can conclude that narrow band vegetation indices calculated from all possible waveband combination from Hyperion data perform much better for winter wheat parameters estimation on a regional level than standard vegetation indices calculated from red and NIR wavebands. Comparing all three index calculations, it was observed that two-band indices calculated according to Eq. 2 performed much better for estimation of aboveground biomass and total nitrogen content with at least 12 % improvement for aboveground biomass and 48 % for plant nitrogen content for winter wheat in the North China Plain. Because satellite image data were acquired at shooting and heading stage with a canopy closure of almost 100 %, the saturation effect was obvious. This saturation effect is pointed out in a flat slope for regression between standard NDVI and aboveground biomass in Fig. 3. Compared to this, the slope of the regression line is much steeper using bands from the NIR and SWIR for index calculation. The results of band combination showed, that the saturation problem occurred for standard vegetation indices can be overcome by using different combinations for narrow band indices.

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