

# CORN FPAR ESTIMATING WITH NEAR AND SHORTWAVE INFRARED BANDS OF HYPERSPECTRAL DATA BASED ON PCA

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## ABSTRACT:

FPAR (Fraction of Absorbed Photosynthetically Active Radiation) is a key parameter in the study on ecosystem function, crop growth monitoring, and so on, it is important to estimate FPAR accurately. Based on the analysis of measured corn hyperspectral and PAR data, the conclusions of this paper are: PCA approach can be used to distill hyperspectral information successfully, two principal components could hold more than 98.464% of the original hyperspectral information. PCA method could estimate FPAR effectively, for analyzing visible and near-infrared band with  $R^2$  of 0.858 and RMSE of 0.110, and analyzing near-infrared and shortwave band with  $R^2$  of 0.868 and RMSE of 0.106. Vegetation indices of (Normalized Difference Shortwave Index) and RSI (Ratio Shortwave Index), with the same structure with NDVI and RVI but calculated in different band, were better for FPAR estimation than NDVI and RVI.  $R^2$  for estimating FPAR of NDSI and RSI are 0.9026 and 0.8951, but 0.8510 and 0.8469 to NDVI and RVI. Near and shortwave hyperspectral reflectance has the great potential for estimating FPAR, which could be good to improve the precision of FPAR estimation.

## 1. INTRODUCTION

FPAR (Fraction of Absorbed Photosynthetically Active Radiation), measures the proportion of available radiation in the specific photosynthetically active wavelengths of the spectrum 400-700nm that the canopy absorbs. FPAR is important detecting index for vegetation water, energy and carbon balance, and a key parameter in the ecosystem productivity model, crop yield model, and so on. (Churkina et al., 1999; Sellers et al., 1997; Lobell et al., 2000)

Now, FPAR were estimated mainly in the empirical models of vegetation indices (Epiphany et al. 1995; Ridao et al. 1998; Eduardo et al., 1998; Daughtry et al., 1992) or the physical transfer models. Normalized difference vegetation index (NDVI) was often used for FPAR estimating of empirical models. Some simple and complicate physical models, such as the CLM (Common Land Model) (Tian et al., 2004), 3-Dimensional physical transfer model (Myneni et al 1999; Knyazikhin et al., 1998a, 1998b), were used.

Hyperspectral data contains abundant spectral information which can express the elaborate characteristic of object. It has been widely used on objects identification and classification, and the estimation of vegetation biophysical and biochemical variables (Lucas et al., 2000; Tong et al., 2001; Song et al, 2006). A series of hyperspectral analyzing techniques such as spectral derivate, spectral unmixing, spectral dimension feature extracting, were investigated for information extraction (Pu and Gong, 2000). The major problem is the high dimensionality of hyperspectral data (Pu and Gong, 2004), and some long wavelength of reflectance has scarcely been utilized. Principal component analysis (PCA) is a classical approach that could compress multivariate data sets to several variables that

preserving most of the information. By far, PCA method has scarcely been used for hyperspectral information compressing (Pu and Gong, 2004), and hardly been used for FPAR estimation, especially in Northeastern China.

Therefore, this paper will introduce PCA approach for hyperspectral reflectance information distilling and FPAR estimating, and studied the near-infrared and shortwave bands for estimating FPAR, based on the measured corn data in Northeastern China.

## 2. BACKGROUND

### 1.1 2.1. Study Area and Sampling

The study site is located in the Changchun and Dehui counties of Jilin province in Northeastern China (latitude 43°47' to 44°53'N, longitude 125°15' to 126°24'E) (see Figure 1). The mean annual temperature is 4.85 °C, the mean annual global radiation is 118.7 kJ/cm<sup>2</sup>, the annual sunlight time is 2648.5 hours, the mean annual precipitation 522 mm. The main growing period of crops is May to September. This uppermost soil type of this area is black soil, which is part of world famous black soil zone of Northeastern China.

The measured data were collected, for four times in Changchun experimental station of Jilin agricultural university on June 15, July 5, July 22 in 2007 and August 19 in 2006, and one time in Dehui county corn field on August 6 in 2007, totally 99 groups data were obtained.

### 1.2 2.2. Canopy Hyperspectral reflectance Measurement

The ASD spectroradiometer of FieldSpec Pro FR was used for measuring corn canopy hyperspectral reflectance, field of view

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is 25°, spectral range is 350–2500 nm, the spectral resolutions of 350–1000 nm and 1000–2500 nm are 3 nm and 10 nm respectively, and the re-sampling interval of reflectance is 1 nm. Spectral data was collected from 10:30 to 13:00, to make sure that the sun elevation angle was above 45°; and keep the fiber probe vertically above corn canopy for 1.5 m. When corn was high in the later period of growing stages, a ladder was used for keeping fiber vertical. It was needed for white board calibrating before collecting data for every sampling to eliminate the weather condition effect.

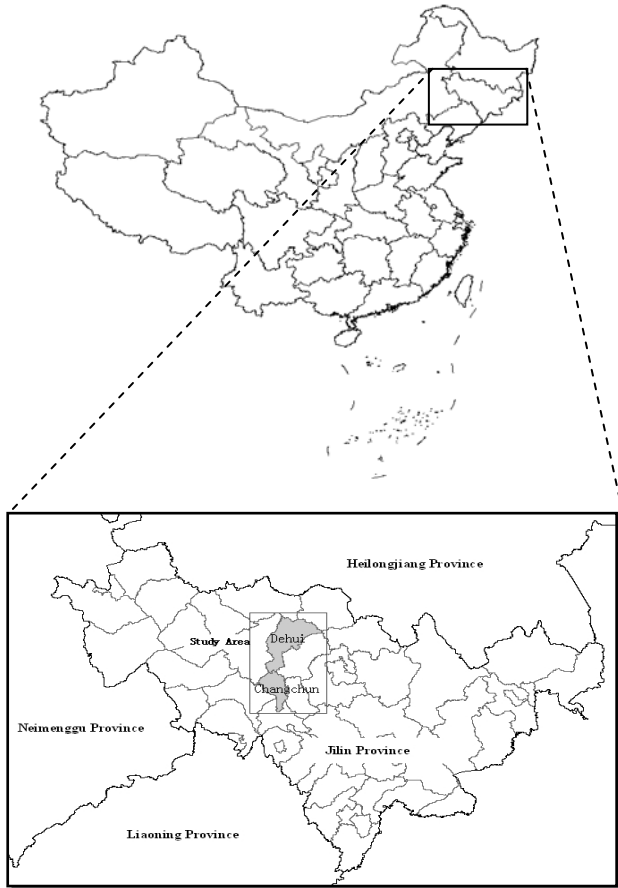


Figure 1. Location of study area

### 1.3 2.3. FPAR Measurement

Photosynthetically Active Radiation (PAR) was measured with LI-191SA linear quantum sensor and LI-250A light meter produced by LI-COR Inc. LI-191SA inductive area is 1m×12.7mm, inductive wavelength ranges from 400nm to 700nm, and with logging unit of  $\mu\text{mol m}^{-2} \text{s}^{-1}$ . Logged data is the averaged PAR in the inductive area, which could reduce the spatial heterogeneity effect. LI-250A logged the result which was read and wrote down manually. Four fractions of PAR data of each sampling were measured, which are incidence PAR above the canopy (PARci), transmitted by the canopy (PARgi), and reflected from the soil (PARgr) and the canopy (PARcr), and FPAR is calculated by the four fractions (Gallo and Daughtry, 1986):

$$FPAR = \frac{(PARci - PARcr) - (PARgi - PARgr)}{PARci} \quad (1)$$

### 3. METHODOLOGY

The normalized difference vegetation index (NDVI) and Ratio vegetation index (RVI) (Rouse et al., 1974; Jordan, 1969) have been the extremely popular spectral vegetation indices for biophysical parameter retrieval. They are given as:

$$NDVI = \frac{(\rho_{NIR} - \rho_{Red})}{(\rho_{NIR} + \rho_{Red})} \quad (2)$$

$$RVI = \frac{\rho_{NIR}}{\rho_{Red}} \quad (3)$$

Where  $\rho_{NIR}$  and  $\rho_{Red}$  are the NIR and red wavelength reflectance.

Principal component analysis is effective at compressing information in multivariate data sets by computing orthogonal projection which maximize the amount of data variance. The object of PCA is to find a lower-dimensional representation that accounts for the major variance of the original dataset.

In this study,  $R^2$  and RMSE were used as the indicating index of the estimating performance for each approach. RMSE was calculated with the following equation:

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (Y_p - Y_m)^2}{n}} \quad (4)$$

where  $Y_p$  is the predicted FPAR,  $Y_m$  is the measured FPAR,  $n$  is the number of sample.

### 4. RESULTS AND DISCUSSION

#### 1.4 4.1 Analysis of the Correlations between FPAR and Hyperspectral Reflectance

As seen from Figure 2, FPAR and reflectance showed good positive correlations in the near-infrared bands, but negative correlations in visible and short wave bands. And the negative correlations with the maximum absolute value of 0.895, were much better than positive correlations with the maximum correlation coefficient of 0.786.

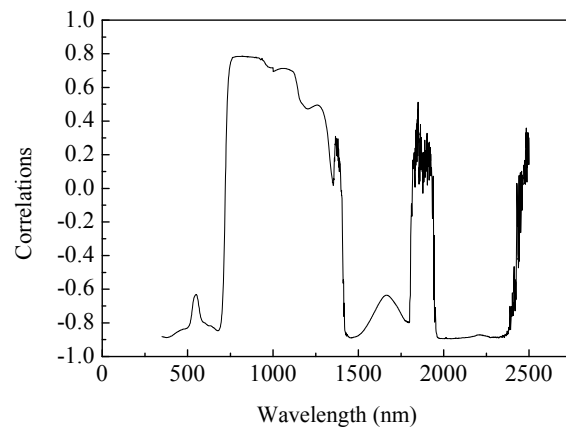


Figure 2. Correlations between FPAR and hyperspectral reflectance

The correlation efficient FPAR and reflectance was different for each wavelength. The decreasing reflectance of shortwave band is similar with visible band changes as the vegetation grows, but the ascend changes for near-infrared bands; and NDVI and RVI are calculated with the red and near-infrared bands, therefore, we replace the red bands with shortwave band for vegetation

index computing, and defined to be NDSI (Normalized Difference Shortwave Index) and RSI (Ratio Shortwave Index), for the same structure as NDVI and RVI respectively.

**1.5 4.2. Correlations between FPAR and NDVI, RVI, NDSI, RSI with the Combinations of Each Wavelength**

To avoid the smart wavelength difference, we re-sampled the 1nm interval hyperspectral reflectance to 2nm, and chose the band of 630nm to 690nm for the visible, 760nm to 1250nm for near-infrared, 1550nm to 1750nm and 2080nm to 2350nm for shortwave band; totally, 58302 combinations (237×246) were calculated for NDSI and RSI, 7626 combinations (246×31) for NDVI and RVI. The correlations of FPAR and NDVI, RVI, NDSI, RSI with the combinations of each wavelength are

shown in Figure 3. We can see from Fig.3 that NDSI and RSI calculated by near-infrared and shortwave band, showed better correlations with FPAR than NDVI and RVI calculated by visible and near-infrared band. The correlations efficient NDSI with FPAR were 0.9146 to 0.9418, and 0.8642 to 0.9343 for RSI; but 0.8933 to 0.9116 and 0.8192 to 0.8574 for NDVI and RVI. Therefore, we could see that shortwave band showed great potential for FPAR estimating. This is due to that shortwave band is controlled by water content of vegetation canopy, and varies much more acutely than visible band.

Band Inputs	Principal Component	Eigen-value	Percent (%)	Cumulative Percent (%)	FPAR Regression	R <sup>2</sup>	RMSE
Visible-infrared	c1	12.073	71.015	71.015	= -9.074c1+3.750c2+0.551	0.858	0.110
	c2	4.666	27.449	98.464			
Infrared-shortwave	c1	11.584	68.142	68.142	= 2.166c1-3.629c2+0.654	0.868	0.106
	c2	5.315	31.266	99.408			

Table 1. Hyperspectral reflectance analysis and FPAR estimation results by PCA approach

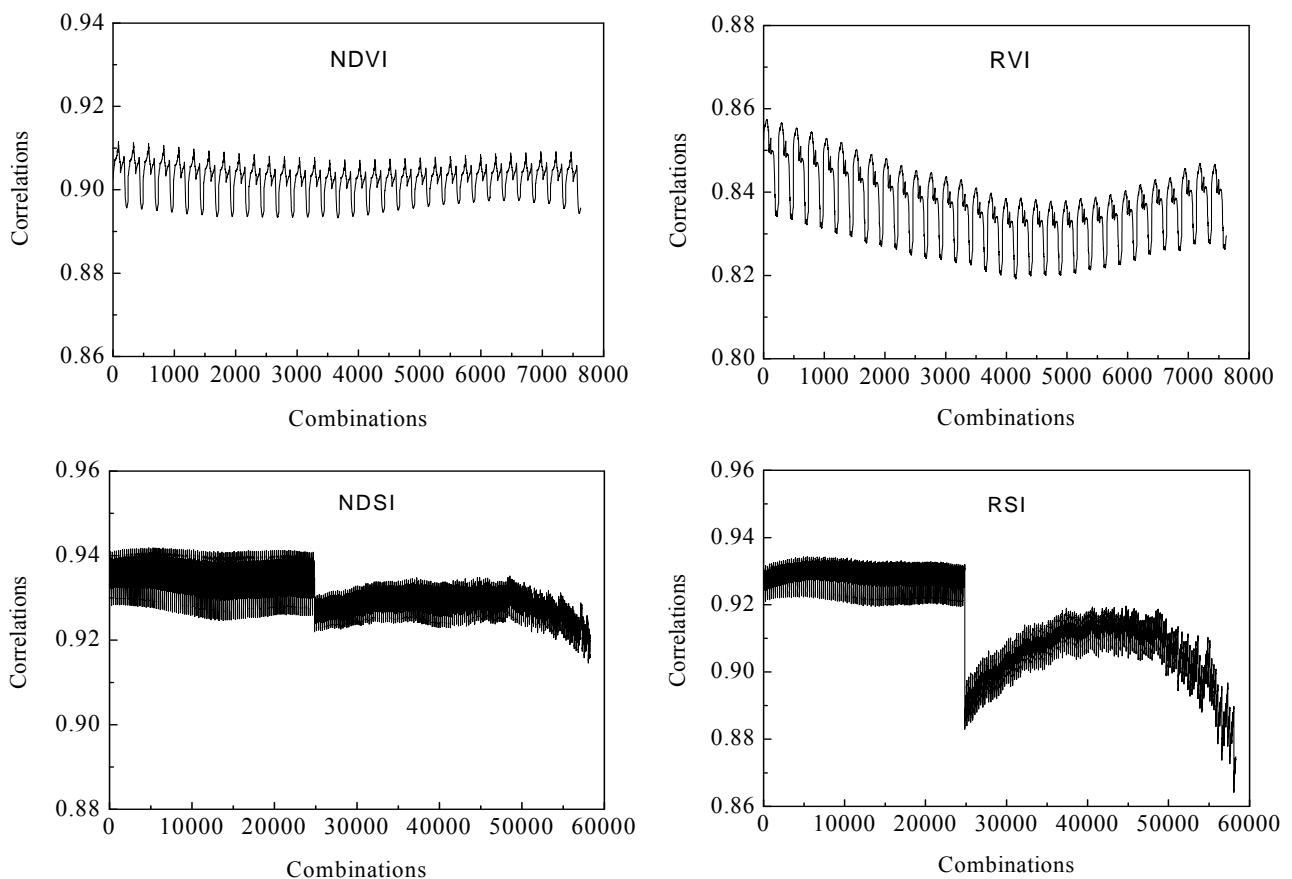


Figure 3. Correlations of FPAR and NDVI, RVI, NDSI, RSI with different wavelength combinations

**1.6 4.3. FPAR Estimating of Vegetation Indices**

On the basis of analysis above, we chose the combinations of each vegetation index with the best correlations efficient for FPAR estimating. The best wavelength combinations for NDVI,

RVI, NDSI, RSI were 630nm and 936nm, 630nm and 868nm, 1588nm and 938nm, 1592nm and 1250nm. The regression results of vegetation indices and FPAR were shown in Figure 4. NDVI and NDSI showed good linear regression with R<sup>2</sup> of 0.8510 and 0.9026, but logarithm regression for RSI and RVI

with  $R^2$  of 0.8951 and 8469. Also, NDSI and RSI showed better performances for FPAR estimating with RMSE of 0.091 and 0.095, than NDVI and RVI with RMSE of 0.112 and 0.114.

#### 1.7 4.4. Hyperspectral Reflectance Analysis and FPAR Estimation by PCA Approach

In this study, visible and near-infrared bands of 17 wavelength, according to MODIS sensor spectral channels, were analyzed by PCA approach, and also near-infrared and shortwave bands

of 17 wavelength analyzed by PCA, the results were shown in Table 1. We could see that PCA approach could compress the 17 wavelength information to two principal components effectively, which keep the information above 98.464%. According to the wavelength contributed to the components, we found that they contained the visible, near-infrared, shortwave band information respectively. And PCA approach showed good FPAR estimating performance with  $R^2$  of 0.858 and 0.868, RMSE of 0.110 and 0.106.

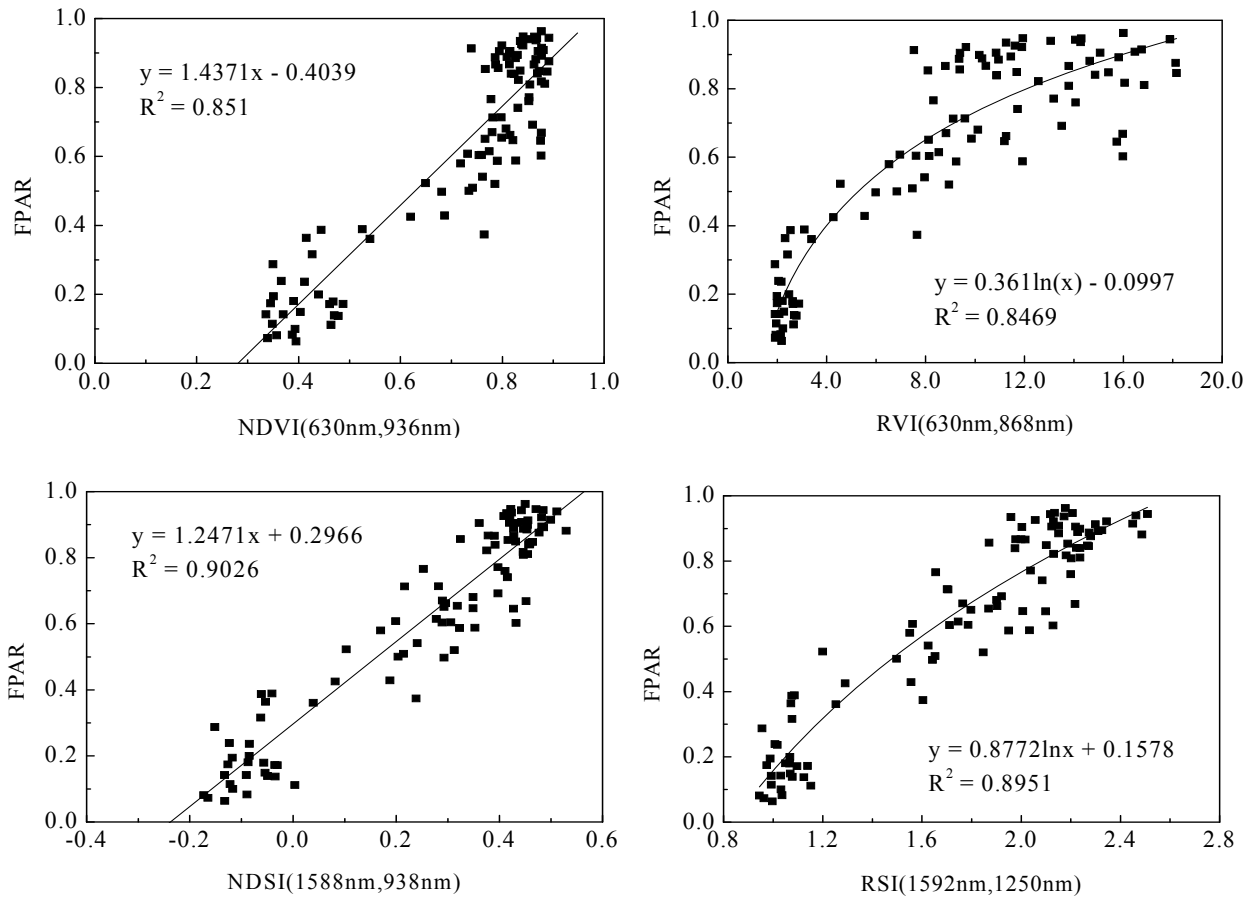


Figure 4. FPAR estimation by NDVI, RVI, NDSI, RSI of best wavelength combination

We can see from the analysis above that, the two components of PCA approach could retain most of the information and PCA approach showed good performance for FPAR estimation. Infrared-shortwave bands analysis by the PCA approach showed good performance than visible and near-infrared bands on FPAR estimation, and similar conclusion could be got from the vegetation index analysis above. This may be due to that shortwave band reflectance is controlled mainly by the water content which plays the important role on photosynthesis and affect the vegetation absorption to PAR (Carter, 1991; Zarco-Tejada et al., 2003), the near and shortwave infrared band of long wavelength is the feedback of canopy FPAR. According to the analysis on the correlations between FPAR and NDVI, RVI, we also could see that the wavelength selection for PCA approach analyzing still need further studies because of the redundant hyperspectral information of adjoining bands.

## 5. CONCLUSIONS

In this paper, based on measured corn data in northeastern China, we studied the correlations of FPAR and NDVI, RVI with different wavelength combinations (from visible to near-infrared and shortwave bands), and two vegetation indices of NDSI and RSI with similar structure of NDVI and RVI, were defined and used for FPAR estimating. This paper also introduced PCA approach for compressing hyperspectral reflectance information and estimating FPAR. The conclusions are: NDSI and RSI calculated by the near-infrared and shortwave bands showed better performance than NDVI and RVI that was computed by the visible and near-infrared bands. PCA approach could compress the hyperspectral reflectance information effectively, and showed great performance for FPAR estimating. From the study of vegetation indices and PCA approaches, that shortwave bands have the great potential for FPAR estimating, could be concluded.

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