# Application of PCA and Canopy Near, Shortwave- Infrared Bands for Soybean and Corn FPAR Estimation in the Songnen Plain, China

Xuguang Tang<sup>1, 2</sup> Kaishan Song<sup>1</sup> Dianwei Liu<sup>1\*\*</sup> Zongming Wang <sup>1</sup> Bai Zhang <sup>1</sup> Fei Yang <sup>1, 2</sup>

1. Northeast Institute of Geography and Agricultural Ecology, CAS, Changchun 130012, China 2. Graduate School of CAS, Beijing 100039, China E-mail:tang11100@163.com Tel: 86-431-85542364

# 1. INTRODUCTION

The fraction of photosynthetically active radiation (FPAR) absorbed by global vegetation is a key state variable in most ecosystem productivity models and in global models of climate, hydrology, biogeochemistry, and ecology. Therefore, how accurately retrieve FPAR will directly influence the estimation of many models and requires special attention. While giving us abundant spectral information, hyperspectral remote sensing also brings forward a question about how to extract more useful information from it and improve the inversion precision, for their high correlations of many bands. This refers to the choice of spectrum bands and the data processing approach.

The major problem is the high dimensionality of hyperspectral data. However, principal component analysis (PCA) could achieve date compression and also reserve the main information. So far, PCA has scarcely been used for distilling hyperspectral information and estimating FPAR or other biophysical and biochemical parameters. This study will try to test the feasibility of principal component inversion (PCI) technique. In addition, many studies have been done on FPAR and other vegetation parameters by the empirical or semi-empirical model with the visible and near-infrared bands (<1250nm). This paper will try to discuss the potential of the near and shortwave-infrared bands (780-2500nm) on FPAR estimating. Though the spatial resolution of MODIS is relatively lower, it could provide free FPAR and many other products with high spectral and temporal resolution. So it is the important data source for research and application, and the band selection for PCI in this study is also based on the characteristic of MODIS sensor.

# 2. MATERIALS AND METHODOLOGY

In this study, we present 69 groups of measured soybean hyperspectral and photosynthetically active radiation data in Songnen Plain, China. 5 times of field spectral and FPAR measurements were performed during the important growing stages of soybean under different fertilizations in 2006 in Changchun study area, and 3 times of field works were conducted during June to September 2007 in Hailun study site. In the first part, comparing

with NDVI and RVI (calculated by visible and near-infrared band), NDSI and RSI were constructed (calculated by near, shortwave infrared band) to estimate FPAR. All vegetation indices were under the best wavelength combinations Table 1). In the second part, based on the characteristic of MODIS sensor, 16 bands of visible and near-infrared before 1250nm, and 16 bands of near and shortwave-infrared between 780nm and 2500nm were analyzed by PCA separately. Then the principal components were used to estimate FPAR. For either method, 39 groups were used to establish the estimating model and the left 30 groups were used to validate it.

Table 1 FPAR estimation by NDVI, RVI, NDSI and RSI of the best combination

Vegetation index	Estimation mo	Validation model (n=30)				
v egetation mucx	Fitting function	$R^2$	RMSE	Fitting function	$R^2$	RMSE
NDVI (936nm,640nm)	y = 1.197x - 0.298	0.83	0.097	y=0.769x+0.715	0.71	0.187
RVI (858nm,630nm)	$y=0.337\ln(x)-0.105$	0.80	0.115	y=0.786x+0.724	0.65	0.213
NDSI (1600nm,940nm)	y = 1.207x + 0.268	0.89	0.078	y = 0.509x + 0.363	0.74	0.108
RSI (1590nm,1240nm)	y = 0.558x - 0.398	0.85	0.089	y = 0.780x + 0.173	0.69	0.171

Note: In the estimation model, y represents FPAR and x is the corresponding vegetation index; in the validation model, y is the predicted FPAR based on the vegetation index method and x represents measured FPAR.

Table 2 FPAR estimation by PCA approach based on hyperspectral reflectance

Band inputs	Principal Componet	Eigen- value	Percent (%)	Cumulative Percent (%)	FPAR Regression(n=39)	$\mathbb{R}^2$	RMSE
Visible, Near- infrared	F1	9.822	61.393	61.393	=-0.674*F1-0.888*F2+0.165	0.85	0.090
	F2	5.086	31.788	93.181	0.074 °F1-0.888 °F2+0.103		
Near, shortwave -Infrared	F1	11.091	69.321	69.321	=2.483*F1+3.034*F2+0.031	0.97	0.082
	F2	4.868	30.426	99.747	=2.485*F1+3.034*F2+0.031	0.87	

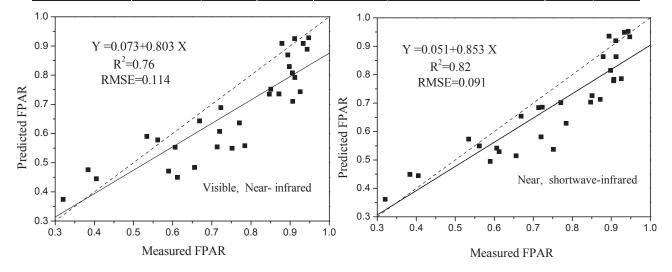


Fig. 1 Validating the fitting relationship between measured FPAR and predicted FPAR by PCA

# 3. RESULTS AND DISCUSSIONS

The conclusions of this study are as follows: 1) PCA method could be used to distill hyperspectral information successfully (Table 2, Fig.1). It would get the visible, infrared factors basically when PCA was used for data analysis. And the first two principal component factors could reserve more than 93.18% of the original information. We also found that the contribution of shortwave-infrared factor was better than the near-infrared, and the near-infrared factor was superior to the visible. For 16 bands of visible and near-infrared before 1250nm, PCA method could estimate FPAR better, with R<sup>2</sup> above 0.85 and RMSE 0.090, than NDVI and RVI, whose R<sup>2</sup> are 0.83, 0.80 and RMSE are 0.097, 0.115, respectively. And for 16 bands of near and shortwave-infrared between 780nm and 2500nm, PCA method could estimate FPAR well too, and its stability was proved to be good (Fig. 1). 2) The near, shortwave-infrared hyperspectral reflectance has great potential for estimating FPAR, which could be good to improve the precision of FPAR estimation. The potential was conducted by two methods of PCA and vegetation index (Table 1, Table 2 and Fig.1). On one hand, two groups of hyperspectral reflectance were analyzed by PCA respectively. The comparison results showed that the near, shortwave-infrared bands had higher precision for estimating FPAR. On the other hand, vegetation indices with the same structure, but different wavelength, NDSI and RSI were better for FPAR estimation than NDVI and RVI. NDSI and RSI could estimate FPAR ideally, whose R<sup>2</sup> were 0.89, 0.85 and RMSE were 0.078, 0.089. 3) On the whole, infrared of longer wavelength has powerful potential for FPAR estimation, which could be more helpful for improving the precision. This should be attributed to the leaf water content. Vegetation photosynthesis is greatly influenced by water, which means the leaf water content that absorbs near and shortwave-infrared bands will influence FPAR of vegetation canopy. So the near and shortwave-infrared bands, to a certain extent, are the feedback of canopy FPAR. When the same research approach was applied to corn in Songnen Plain of China, the above conclusions were all justified.

#### 4. REFERENCES

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