# LAI ESTIMATION OF WINTER WHEAT USING FOUR SPECTRAL INDICES

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## ABSTRACT

The aim of this paper was to apply spectral index to estimate winter wheat LAI and further to compare prediction accuracy and stability of four proposed typical spectral indices based on four kinds of resampling multispectral and hyperspectral sensors data. The results show that VIUPD has the best prediction accuracy and stability for estimation of winter wheat LAI on the basis of four different resampling sensors data, which reaffirms that VIUPD is comparatively sensor independent and illustrates its potential ability in the area of estimating vegetation biochemical parameters.

## 1. INTRODUCTION

LAI is a crucial parameter determined by vegetation canopy structure and a basic quantity indicating crop growth situation which is defined as half leaf surface per unit ground surface area, can be used to infer terrestrial ecosystem, estimate net primary production (NPP) and ecological processes(Liangpei and Lifu 2011; Tong et al. 2006; Yao et al. 2008). Many studies shows that timely and accurately inversing crop LAI using remote sensing plays a significant role in plant growth and yield estimating and crop pests monitoring.

In precious studies, the spectral indices based on experience/semi-empirical method have been widely used due to its simple and quick retrieval characteristics(Hatfield and Prueger 2010). Therefore, a numbers of investigations have studied the spectral indices which have high sensitivity to LAI to estimate the crop LAI, and that the relationship between spectral reflectance and vegetation LAI is often modeled via the use of spectral indices(Elvidge and Chen 1995; Gong et al. 2003; Wang et al. 2005).

Many studies have focused on the optimum band selection and spectral indices constitution in order to improve the prediction accuracy, but ignored the diversity of estimation stability of spectral indices that was caused by the spectral response features of particular sensors(Broge and Leblanc 2001). The identical spectral index derived from diverse sensors will exhibit discrepant prediction accuracy and stability when estimating vegetation LAI.

This study was attempt to apply SIs method to estimate winter wheat LAI and further to compare prediction accuracy and stability of four proposed typical SIs based on four kinds of resampling multispectral and hyperspectral sensors data.

## 2. METHODOLOGY

Due to the difference of revisit time of remote sensors and the complexity of weather situation when satellite transiting, so many difficulties were arose in the acquisition of four kinds of sensors data synchronously. In this study, the measured spectra data from PSR-3500 spectroradiometer were resampled to simulated reflectance data of Landsat-TM7, Hyperion, ASTER and IKONOS sensor respectively, using the Gaussian spectral response function,(Changping et al. 2010) which can be derived by Equation (1).

$$f\left(x\right)=\frac{1}{\sigma\sqrt{2\pi}}e^{\frac{(x-\mu)^2}{2\sigma^2}} \tag{1}$$

Where $\mu$ is expected value and stands for the central wavelength of each function. $\sigma$ is standard deviation used to calculate $t$. $t$ is the distance from both ends to the center of each Gaussian function. The band numbers after resampling is the numbers of Gaussian function. The spectral values after sampling are the integration of each Gaussian in interval $[\mu - t, \mu + t]$.

We selected Normalized Difference Vegetation Index (NDVI), Triangle Vegetation Index (TVI), Modified Soil-adjusted Vegetation Index (MSAVI). Additionally, we added the vegetation spectrum of red edge 705nm and 750nm into index NDVI because SIs incorporated the red edge provided a reliable performance in the application of LAI estimate. And a new vegetation index, based on the universal pattern decomposition method (VIUPD), which was derived from the universal pattern decomposition method (UPDM), was introduced into this study.

## 3. EXPERIMENTAL DATA

The experiment were conducted in Xiao Tangshan national demonstrated sites for precision agriculture (40°00′-40°21′N,116°34′-117°00′E), in Beijing of China, on May 2$^{nd}$ 2013, when was just at the jointing stage of winter wheat. Twenty-four sample plots, each of which distribution area is 1m$^2$, were selected for the measurement of LAI and spectral reflectance in the experiment area

Top of canopy spectral signatures of winter wheat were measured using Portable Spectroradiometer 3500 (PSR-3500) from 10 a.m. to 2 p.m. in clear sunshine. The target reflectance from region of 350-1,000 nm were used and calculated based on the calibration measurements of a white panel. The sensor, with a field of view of 25 °,was held in a zenith orientation 55cm above the canopy, which allowed coverage of a circular area with a radius of ~12cm. Spectral measurements were conducted randomly at four sites in each sample plot and were averaged to represent the mean reflectance of whole canopy. Based on the gap fraction methodology, the LAIs of winter wheat were measured using a LAI-2200 plant canopy analyser (LI-COR, NE, USA) directly after the spectral measurement under the shadowed conditions(Breda 2003).

## 4. RESULTS

To compare the accuracy and stability of SIs for estimating LAI, a linear regression was used to develop regression model between LAI and each of SIs mentioned above.

The performances of four SIs were evaluated by comparing the diversity in coefficient of determination ($R^2$) and root mean squared error (RMSE). The higher the $R^2$ and the lower the RMSE, the greater the accuracy and precision of the SIs to estimate LAI(Li et al. 2010). The RMSE was calculated using Equation (2):

$$RMSE = \sqrt{\frac{1}{M}\sum_{i=1}^{M}\left[Z^{*}(S_i) - Z(S_i)\right]^{2}} \qquad (2)$$

where $Z^{*}(S_i)$ and $Z(S_i)$ was the predicted and measured value respectively, M was the numbers of samples.

## 4.1 Regression Between Spectral Indices and LAI Based on Simulated TM Sensor Data

In the linear regression equation between SIs and LAI value, correlation coefficients $R^2$ values varied from 0.6911 to 0.9158 and the RMSE varied from 0.21 to 0.40 for the SIs selected. Under the simulated TM data, VIUPD stood first for estimating LAI with a $R^2$ of 0.9158, followed by NDVI and MSAVI showed a comparatively good retrieval accuracy with $R^2$ of 0.8042 and 0.8024, respectively. And the TVI we obtained were exceed 0.64.
From the figure 1, it is evident that all four selected SIs revealed a reliable performance ($R^2$>0.69 and RMSE<0.41) to estimate LAI of winter wheat. The index TVI had the largest RMSE of 0.40 for LAI estimation. The spectral indices NDVI and MSAVI were comparable to predict LAI (RMSE lower than 0.33). The index VIUPD had the highest accuracy for LAI estimation (with RMSE of 0.21). So overall, all SIs tested in this study were considered as the good estimator in the estimation of LAI, but yet the best one is VIUPD.

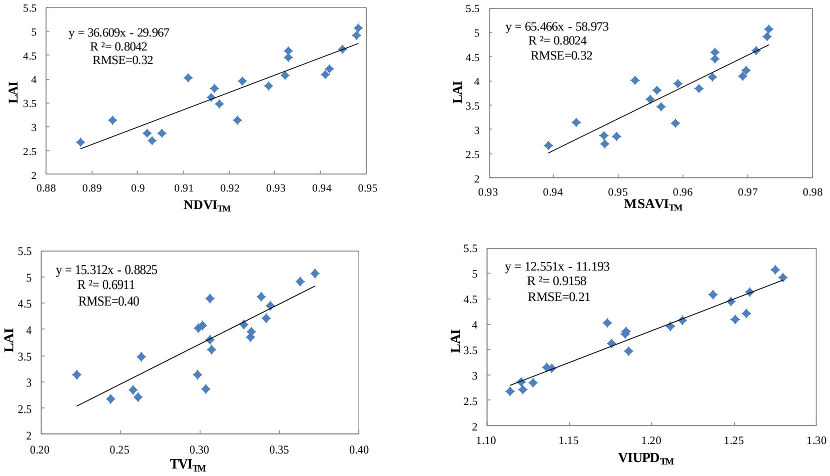


**Figure 1. The regression relationship between indices and LAI for $NDVI_{TM}$, $TVI_{TM}$, $MSAVI_{TM}$ and $VIUPD_{TM}$ based on the simulated TM data**

## 4.2 Regression Between Spectral Indices and LAI Based on Simulated Hyperion Sensor Data

The correlation coefficients $R^2$ values varied from 0.5615 to 0.8916 and the RMSE varied from 0.24 to 0.48 for the SIs selected. VIUPD again ranked first for estimating LAI with a $R^2$ of 0.8916, followed by MSAVI showed a slightly lower $R^2$ of 0.8248 under the simulated Hyperion data. For the indices TVI and NDVI, a moderate $R^2$ were presented with 0.6307 and 0.5615, respectively.
From the figure 2, it is apparent that the index VIUPD had the lowest RMSE of 0.24, revealing its good performance to estimate LAI of winter wheat. For index MSAVI, it can be thought as a good estimator with RMSE of 0.30 for predicting LAI. The indices TVI and NDVI were of comparable precision to predict LAI, with RMSE of 0.44 and 0.48, respectively.

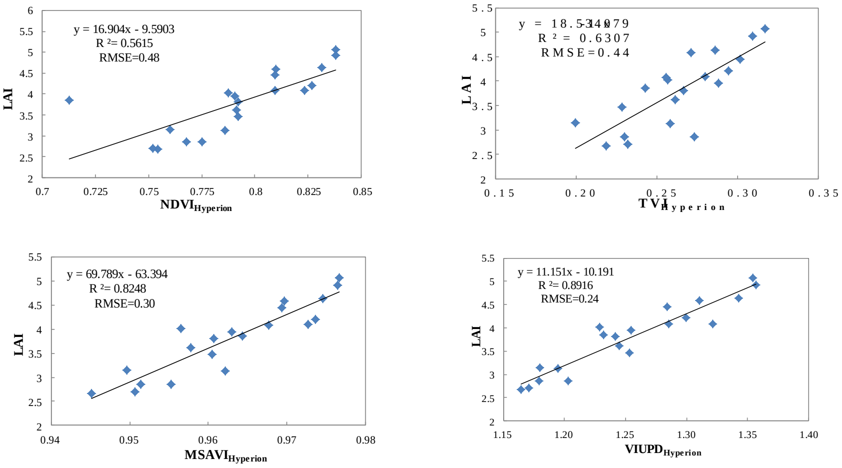


**Figure 2. The regression relationship between indices and LAI for $NDVI_{Hyperion}$, $TVI_{Hyperion}$, $MSAVI_{Hyperion}$ and $VIUPD_{Hyperion}$ based on the simulated Hyperion data**

## 4.3. Regression Between Spectral Indices and LAI Based on Simulated ASTER Sensor Data

From the figure 3, it is obvious that four selected SIs expressed a dependable performance ($R^2$>0.69 and RMSE<0.41) to estimate LAI under simulated ASTER data. VIUPD had the lowest RMSE of 0.23, showing its best performance to estimate LAI of winter wheat. Therefore, VIUPD was the most reliable predictor in the prediction of LAI, using the resampling ASTER data.

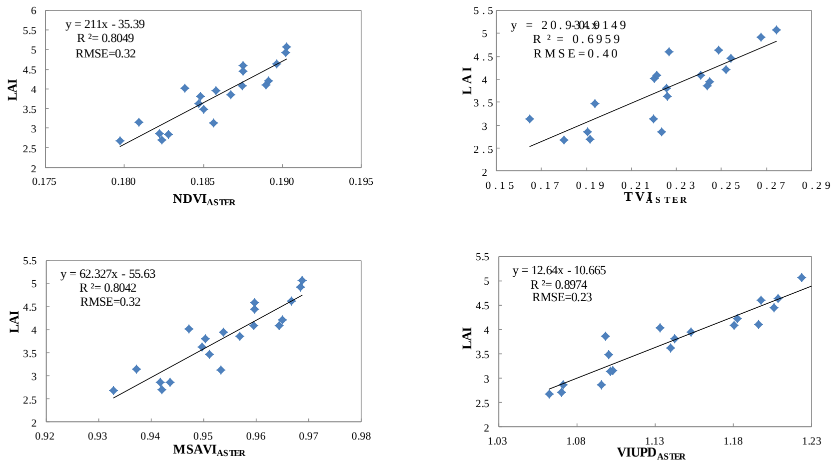


**Figure 3. The regression relationship between indices and LAI for $NDVI_{ASTER}$, $TVI_{ASTER}$, $MSAVI_{ASTER}$ and $VIUPD_{ASTER}$ based on the simulated ASTER data**

## 4.4 Regression Between Spectral Indices and LAI Based on Simulated IKONOS Sensor Data

The figure 4 demonstrated that VIUPD again ranked first for estimating LAI with a $R^2$ of 0.8213, followed by MSAVI showed a slightly lower $R^2$ of 0.8147. For the indices TVI, a moderate $R^2$ were presented with 0.70. The index NDVI showed a lowest $R^2$ in the estimation of LAI ($R^2$=0.5898), which were significantly lower than the precision of LAI retrieval, using the simulated TM and ASTER data. Consequently, VIUPD still was the most reliable predictor in the prediction of LAI under the simulated IKONOS data.

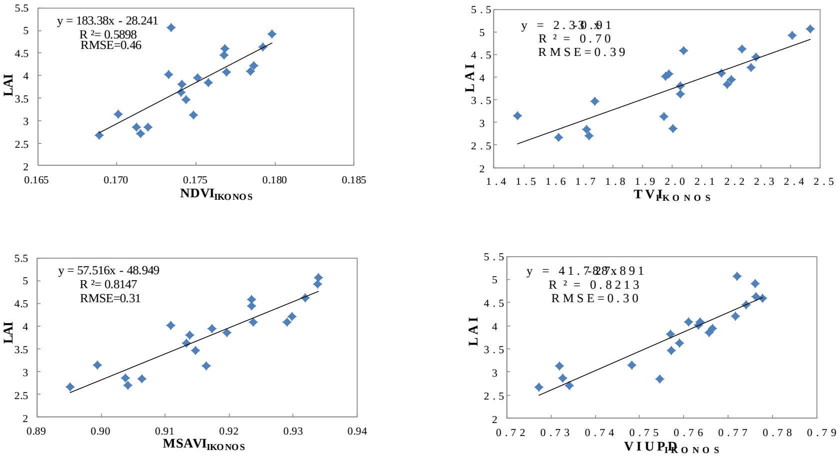


**Figure 4. The regression relationship between indices and LAI for $NDVI_{IKONOS}$, $TVI_{IKONOS}$, $MSAVI_{IKONOS}$ and $VIUPD_{IKONOS}$ based on the simulated IKONOS data**

## 5. CONCLUSIONS

In this investigation, four indices, including three common narrow-band spectral indices and sensor-independent index VIUPD, were compared for the estimation of winter wheat LAI. And the significant differences of retrieval ability of four indices were found in the LAI estimation based on four kinds of resampling sensors data.

Of all the SIs, VIUPD has the best performance to estimate vegetation LAI based on the reflectance data of different simulated sensors with the $R^2$ of 0.8213-0.9158 and the RMSE of 0.21-0.30, which reaffirms that VIUPD is comparatively sensor independent. MSAVI also was a good LAI estimator in terms of the lowest sensitivity to canopy effects and soil spectral properties, which means that the separation of vegetation and background especially soil, or the elimination of effects of soil background, was greatly important for the precision of predicting LAI. Other two SIs show a unstable prediction accuracy according to different sensors. VIUPD introduced in this study exhibits the best performance of estimating winter wheat LAI, which illustrates its potential ability in the area of estimating vegetation biochemical parameters.

## 6. ACKNOWLEDGEMENT

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