

An evaluation of prediction accuracy and stability of a new vegetation index for estimating vegetation leaf area index

Hailing Jiang^{a,b}, Lifu Zhang^{*b}, Hang Yang^b, Xiaoping Chen^c, Shudong Wang^b, Xueke Li^b, Kai Liu^d
^aInstitute of Remote Sensing and GIS, Peking University, Beijing 100871, China; ^bInstitute of Remote Sensing and Digital Earth, Chinese Academy of Sciences, Beijing 100101, China; ^cHarbin Institute of Technology Shenzhen Graduate School, Shenzhen, 518055, China; ^dInstitute of Geographic Sciences and Natural Resources Research, Chinese Academy of Sciences, Beijing 100101, China

ABSTRACT

LAI is a crucial parameter and a basic quantity indicating crop growth situation. Empirical models comprising spectral indices (SIs) and LAI have widely been applied to the retrieval of LAI. SI method already has exhibited feasibility in the estimation of vegetation LAI. However, it is largely subject to the inconsistency from different remote sensors which have varied specifications, such as spectral response features and central wavelength. To address this issue, a new vegetation index (VIUPD) based on the universal pattern decomposition method was proposed. It is expressed as a linear sum of the pattern decomposition coefficients and features in sensor-independency. The aim of this study was to evaluate the prediction accuracy and stability of VIUPD for estimating LAI, compared with three other common-used SIs. In this study, the measured spectra were resampled to simulated TM multispectral data and Hyperion hyperspectral data respectively, using the Gaussian spectral response function. The three typical SIs chosen were including NDVI, TVI and MCARI, which were constructed with the sensitive bands to the LAI. Finally, the regression equations between four selected SIs and LAI were established. The best index evaluated using the simulated TM data was VIUPD which exhibits the best correlation with LAI ($R^2=0.92$) followed by NDVI ($R^2=0.80$). For the simulated Hyperion data, VIUPD again ranks first with $R^2=0.89$, followed by TVI ($R^2=0.63$). Meanwhile, the consistence of VIUPD also was studied based on simulated TM and Hyperion sensor data and the R^2 reached to 0.95. It is demonstrated that VIUPD has the best accuracy and stability to estimate LAI of winter wheat whether using simulated TM data or Hyperion data, which reaffirms that VIUPD is comparatively sensor independent.

Keywords: retrieval of leaf area index, spectral index, VIUPD, data resampling, regression analysis, prediction accuracy and stability

1. INTRODUCTION

Remote sensing has provided valuable information for estimation of various agronomic parameters in the precision agriculture, which also has the ability of field-scale monitoring without destructive sampling of the crop¹. In particular, the spectral reflectance from narrow band of vegetation leaves and canopies based on multispectral and hyperspectral sensors has proven promising for estimating a large variety of eco-physiological parameters including vegetation light use efficiency (LUE), leaf water content and the leaf area index (LAI)². LAI is a basic quantity indicating crop growth

*zhanglf@irsa.ac.cn; phone:010-64839450; fax:01064839450; irsa.ac.cn

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). 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 monitoring³.

In precious studies, there are two typical methods for estimating vegetation LAI, including the experience/semi-empirical method and the radiative transfer model method. However, compared to the former method, the latter one is often restricted in practical applications owing to that it involves complex algorithms and difficulties in acquisition of input parameters. In contrast, the spectral indices based on experience/semi-empirical method have been widely used due to its simple and quick retrieval characteristics⁴. Spectral index (SI) has been developed as the algebraic combination using two or more bands of multispectral or hyperspectral bands which are designed to highlight a particular property of vegetation. 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 indices⁵.

Elvidge and Chen (1995) calculated the SIs which were linear combinations of near infrared (NIR) and visible red reflectance and have been found to be well correlated with canopy structure, LAI, and absorbed photosynthetic active radiation (APAR)⁶. Broge and Leblanc (2001) compared the prediction power and stability of broadband and hyperspectral SIs for estimation LAI and canopy density⁷. Pisek and Chen (2007) pointed out that various SIs derived from broadband sensors were used with regard to their capacity to retrieval biochemical parameters of vegetation, including LAI and chlorophyll content⁸. Wu (2010) established the spectral indices that incorporated red edge portion 705 nm and 750 nm to estimate LAI of wheat reliably⁵.

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. The identical spectral index derived from diverse sensors will exhibit discrepant prediction accuracy and stability when estimating vegetation LAI. The aim of this study was to compare the prediction accuracy and stability of four proposed typical SIs and further to evaluate the performance of VIUPD in the estimation of LAI of winter wheat based on resampling multispectral and Hyperion hyperspectral sensor data.

2. MATERIALS AND METHODS

2.1 Acquisition of Spectral Data and LAI

The experiment were conducted in Xiao Tangshan national demonstrated sites for precision agriculture (40°00'-40°21'N, 116°34'-117°00'E), in ChangPing District in Beijing of China, on May 2nd 2013, when was just at the jointing stage of winter wheat. Twenty-four sample plots, each of which distribution area is 1m², were selected for the measurement of LAI and spectral reflectance in the experiment area irrigated by four various treatments and six replications. Details of the irrigation treatments are exhibited in table1.

Table1. The irrigation treatments to experiment areas selected

Number	Irrigation treatment
1	before sowing(60kg)
2	before sowing(30kg) +before freezing(30kg)
3	before sowing(30kg) +before freezing(30kg)+at erecting stage(60kg)+flowering stage(60kg)
4	before sowing(30kg)+before freezing(30kg)+jointing stage(60kg)+flowering stage(60kg)

Top of canopy spectral signatures of winter wheat were measured using Portable Spectroradiometer 3500 (PSR-3500, Spectral Evolution, Inc. USA) from 10 a.m. to 2 p.m. in clear sunshine. This Spectroradiometer sensor acquires spectra in the range of 350-2500 nm using a 512-element Si array and the spectral resolution is 3.5 nm for the spectral region of 350-1,000 nm and 10 nm for the 1,000-1,500 nm region and 7 nm for the 1,500-2,100 nm region. In this study, 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 55 cm above the canopy, which allowed coverage of a circular area with a radius of ~12 cm. Spectral measurements were conducted randomly at four sites in each sample plot and were averaged to represent the mean reflectance of whole canopy⁹.

Based on the gap fraction methodology, the LAI values of winter wheat were measured using a LAI-2,200 plant canopy analyser (LI-COR, NE, USA) directly after the spectral measurement under the shadowed conditions¹⁰. Measurements were carried out considering the instrument calibration that the hemispherical FOV was least impacted by the experiment setup and conditions. The mean LAI value of each sample plot was averaged over two individual measurement.

2.2 Resampling of Spectral Reflectance Data

The definition of spectrum resampling is that the spectrums from spectral library or ground measurement were matched with other known sensor spectrum or spectral source.

In this study, the measured spectra data from PSR-3500 spectroradiometer were resampled to the simulated Landsat-TM7 and Hyperion sensor data, respectively, using the Gaussian spectral response function which can be derived by Equation (1).

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

Where μ is expected value and stands for the central wavelength of each function. σ 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 resampling are the integration of each Gaussian in interval $[\mu - t, \mu + t]$.¹¹

PSR spectrums were resampled to TM six bands spectral in accordance with the spectral response features of Landsat-TM7. The spectral range of Hyperion sensor is from 355.59 to 2,577.08 nm but PSR instrument is only 339.20-2,501.89 nm. Due to the spectral region of resampled Hyperion sensor exceed PSR original range, bad bands of 2501.89-2577.08 nm must be deleted and then the final numbers of Hyperion band was 234.

2.3 Spectral Indices Selection and Calculation

The set of SIs used in this study comprised two categories of indices: the common-used SIs and VIUPD. The common-used SIs have been widely applied and provide reliable predictions of estimating vegetation canopy characteristics including chlorophyll concentration, LAI, water content and biomass. VIUPD is a sensor-independent index, which has been proved to be sensitive to vegetation signal¹².

Three different common-used SIs we selected are Normalized Difference Vegetation Index (NDVI), Triangle Vegetation Index (TVI) and Modified Transformed Chlorophyll Absorption Ratio Index (MCARI). In this study, we added the vegetation spectrum of red edge 705 nm and 750 nm into index NDVI because SIs incorporated the red edge provided a reliable performance in the application of LAI estimation.

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 the current study. In order to acquire more detail information of vegetation change, a supplementary pattern of yellow-leaf was added into the UPDM^{12,13}. Therefore the reflectance data of every pixel obtained from kinds of sensors was decomposed into four spectral patterns of water, vegetation, soil and yellow-leaf as follows:

$$R_i \rightarrow C_w \cdot P_w(i) + C_v \cdot P_v(i) + C_s \cdot P_s(i) + C_4 \cdot P_4(i) \quad (2)$$

Where R_i was the reflectance data of band i measured by the ground spectroradiometer, aircraft or satellite sensor for any samples, C_w , C_v , C_s and C_4 were the decomposition coefficients, and $P_w(i)$, $P_v(i)$, $P_s(i)$ and $P_4(i)$ were the standard spectral patterns of pure water, vegetation, soil and yellow-leaf for band i . $P_k(i)$ ($k = w, v, s, 4$) which stands for the four kinds of standard spectral patterns¹³, is defined by

$$P_k(i) = \frac{\int_{\lambda_s(i)}^{\lambda_e(i)} P_k(\lambda) d\lambda}{\int_{\lambda_s(i)}^{\lambda_e(i)} d\lambda} \quad (k = w, v, s, 4) \quad (3)$$

where $\lambda_s(i)$ and $\lambda_e(i)$ represent the starting and ending wavelength of band i respectively, and $P_k(\lambda)$ is stand spectral pattern of continuous wavelength λ , and $\int_{\lambda_s(i)}^{\lambda_e(i)} d\lambda$ is the wavelength width of i . VIUPD expressed as a linear sum of the pattern decomposition coefficients, was calculated as

$$\text{VIUPD} = \frac{(C_v - 0.1 \times C_s - C_4)}{(C_w + C_v + C_s)} \quad (4)$$

To calculate VIUPD of two simulated sensors, four standard coefficients file concluding water, vegetation, soil and yellow-leaf, were firstly resampled to each simulated sensor, and then was applied to calculation under MATLAB.

Details of three common-used SIs related to vegetation LAI estimation for this study are listed in Table 2.

Table 2. The common narrow-band spectral indices used in this study

Spectral index	Index Name	Formulation	References
<i>NDVI</i>	Normalized Difference Vegetation Index	$NDVI = (R_{NIR} - R_R) / (R_{NIR} + R_R)$	Quan Wang <i>et al.</i> 2005
<i>TVI</i>	Triangle Vegetation Index	$TVI = 0.5 * [120 * (R_{750} - R_{550}) - 200 * (R_{670} - R_{550})]$	Broge and Leblanc 2001
<i>MCARI</i>	Modified Transformed Chlorophyll Absorption Ratio Index	$MCARI = [(R_{700} - R_{670}) - 0.2(R_{700} - R_{550})](R_{700} / R_{670})$	Daughtry <i>et al.</i> 2000

Based on the resampling Landsat-TM spectral data, for $NDVI_{TM}$, the reflectance of band TM3 and TM4 was assigned to R_R and R_{NIR} respectively. For TVI_{TM} , band TM2, TM3 and TM4 were selected to calculate R_{550} , R_{670} and R_{750} . For $MCARI_{TM}$, R_{TM2} , R_{TM3} and $(R_{TM3} + R_{TM4}) / 2$ were equal to the SIs calculation for R_{550} , R_{670} and R_{700} respectively. The details of above SIs formulas were listed in Table3.

Table 3. The formulas of three spectral indices after resampling to TM

Spectral index	Formulation
$NDVI_{TM}$	$NDVI_{TM} = (TM_4 - TM_3) / (TM_4 + TM_3)$
TVI_{TM}	$TVI_{TM} = 0.5 * [120 * (TM_4 - TM_2) - 200 * (TM_3 - TM_2)]$
$MCARI_{TM}$	$MCARI_{TM} = [(R_{TM3} + R_{TM4}) / 2 - R_{TM3}) - 0.2((R_{TM3} + R_{TM4}) / 2 - R_{TM2})]((R_{TM3} + R_{TM4}) / 2 / R_{TM3})$

Based on the resampling Hyperion spectral data, the SIs we selected were calculated. For $NDVI_{Hyperion}$, the reflectance of $(R_{701} + R_{711}) / 2$ and R_{752} were assigned to R_R and R_{NIR} respectively. For $TVI_{Hyperion}$, $(R_{548} + R_{559}) / 2$, R_{671} and R_{752} were selected to calculate R_{550} , R_{670} and R_{750} . For $MCARI_{Hyperion}$, $(R_{548} + R_{559}) / 2$, R_{671} and R_{701} were equal to the SIs calculation for R_{550} , R_{670} and R_{700} respectively. The details of above SIs formulas were listed in Table4.

Table 4. The formulas of three spectral indices after resampling to Hyperion

Spectral index	Formulation
$NDVI_{Hyperion}$	$NDVI_{Hyperion} = (R_{752} - (R_{701} + R_{711}) / 2) / (R_{752} + (R_{701} + R_{711}) / 2)$
$TVI_{Hyperion}$	$TVI_{Hyperion} = 0.5 * [120 * (R_{752} - (R_{548} + R_{559}) / 2) - 200 * (R_{671} - (R_{548} + R_{559}) / 2)]$
$MCARI_{Hyperion}$	$MCARI = [(R_{701} - R_{671}) - 0.2(R_{701} - (R_{548} + R_{559}) / 2)](R_{701} / R_{671})$

3. RESULTS AND DISCUSSION

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 these 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 LAI¹⁴. The RMSE was calculated using Equation (5):

$$RMSE = \sqrt{\frac{1}{M} \sum_{i=1}^M [Z^*(S_i) - Z(S_i)]^2} \quad (5)$$

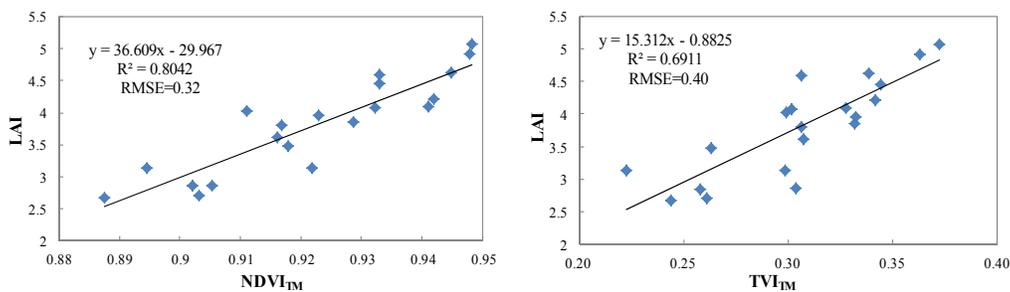
where $Z^*(S_i)$ and $Z(S_i)$ was the predicted and measured value respectively, M was the numbers of samples.

3.1 Regression Between Spectral Indices and LAI Based on Simulated TM 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 showed a comparatively good retrieval accuracy with R^2 of 0.8042. For the MCARI index, a moderate R^2 of 0.7263 was observed.

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, and MCARI had a slightly lower RMSE at 0.38. The spectral index NDVI was 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 based on the simulated TM data, but yet the best one is VIUPD.



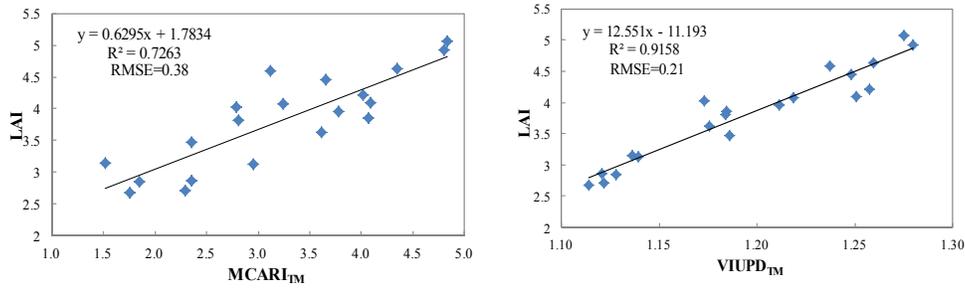


Figure 1. The regression relationship between indices and LAI for NDVI_{TM}, TVI_{TM}, MCARI_{TM} and VIUPD_{TM} based on the simulated TM data

3.2 Regression Between Spectral Indices and LAI Based on Simulated Hyperion Data

To compare the relationship between SIs and LAI values, a linear regression equation was set up in this research. The correlation coefficients R^2 values varied from 0.3948 to 0.8916 and the RMSE varied from 0.24 to 0.56 for the SIs selected.

Of all the SIs tested, VIUPD again ranked first for estimating LAI with a R^2 of 0.8916 under the simulated Hyperion data. For the indices TVI and NDVI, a moderate R^2 were presented with 0.6307 and 0.5615, respectively. However, MCARI exhibited a lowest R^2 in the estimation of LAI ($R^2 < 0.4$), which were significantly lower than the precision of LAI retrieval using the simulated TM data.

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. The indices TVI and NDVI were of comparable precision to predict LAI, with RMSE of 0.44 and 0.48, respectively. For index MCARI, the largest RMSE were obtained (0.56). Therefore, VIUPD was the most reliable predictor in the prediction of LAI under the simulated Hyperion data.

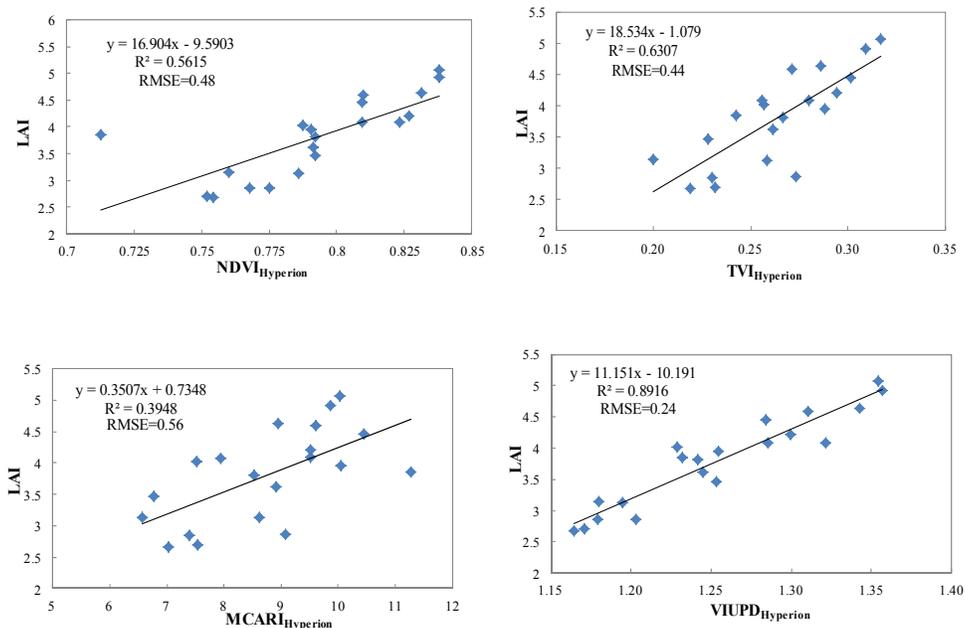


Figure 2. The regression relationship between indices and LAI for NDVI_{Hyperion}, TVI_{Hyperion}, MCARI_{Hyperion} and VIUPD_{Hyperion} based on the simulated Hyperion data

3.3 Summaries and Analysis

Based on the above associations between four SIs and LAI values, the precision of SIs in the prediction of wheat LAI were summarized and compared.

Figure 3 exhibits that four SIs selected in this paper presents variant retrieval precision from TM and Hyperion simulated sensors data. LAI was accurately estimated by VIUPD from two selected simulated sensor data ($R^2 > 0.89$). For the index TVI, even though there was little variation in the retrieval accuracy of R^2 values in the estimation of LAI based on selected data, its precision for predicting LAI still was lower than VIUPD. For indices NDVI and MCARI, their retrieval precision were reliable aimed at parts of chosen sensors, but terrible directed at another selected simulated sensors. For example, MCARI showed a good performance when predicting LAI based on the resampling TM sensor data, but expressed the worst ability to estimate LAI based on the resampling Hyperion sensor data only with R^2 of 0.3948.

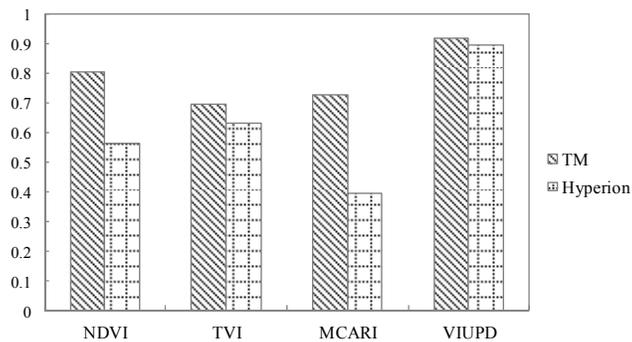


Figure 3. The comparison of retrieval accuracy and stability of four spectral indices for estimating winter wheat LAI

Above all, VIUPD exhibits the best prediction accuracy and stability when estimating LAI of winter wheat. Due to its computation from decomposition with four UPDM coefficients of C_w , C_v , C_s and C_4 , VIUPD is a linear function and finally is normalized by the total reflectance values. The four UPDM coefficients has the characteristic of sensor-independent, thus VIUPD inherits this special features from the coefficients of UPDM^{12,13}. The traditional indices NDVI, TVI and MCARI selected in this study, are calculated with some feature bands including red band (R), green band (G), near-infrared band (NIR) and so on, while VIUPD is calculated with all the observed wavelengths. Therefore VIUPD presents more excellently in the predicting LAI than other five indices.

TVI is conducted by the total triangle area that was formed by the reflectance of three wavelengths including 550 nm, 670 nm and 750 nm. The value of index TVI will be increased because of increasing chlorophyll absorption¹⁵. As a result, it was relatively accurate and stable to estimate LAI with an average value of prediction R^2 of 0.66 based on two simulated sensor data.

NDVI is a simple but most well-known spectral index in the estimation of vegetation variables, which was computed with two bands reflectance, comprised red band and near-infrared band¹⁵. In the current study, the reflectance of red edge 705

nm and 750 nm were selected to form the NDVI. Consequently, NDVI has already been found to perform the reliable ability in the retrieval LAI of winter wheat, showing the average R^2 of 0.68.

As an improved version of MCARI, was incorporated with near-infrared wavelengths to increase the sensitivity to LAI of crop and reduce the impact of reflectance of soil background¹⁶. In our research, it exhibits a good ability to estimate LAI when using the simulated TM sensor data, but yet is thought as a worst estimator based on the resampling Hyperion data. Therefore, the instability of index MCARI for predicting LAI are found to predict LAI of winter wheat.

3.4 The consistence of VIs based on the different sensors

From the above results of VIs in the estimation of LAI, VIUPD had the best prediction accuracy and stability. The consistence of VIUPD was studied based on the simulated sensors we selected.

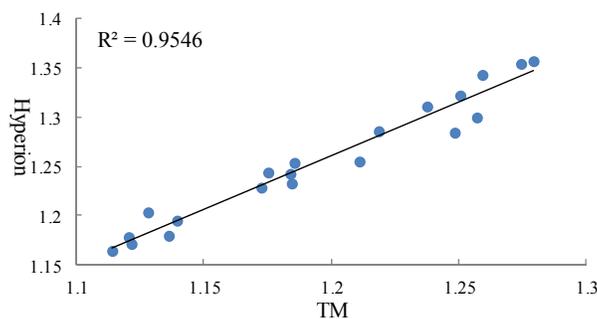


Figure 4. The consistence of VIUPD based on simulated TM and Hyperion sensors

As shown in Figure 4, VIUPD has great consistence based on multispectral and hyperspectral sensors, which reaffirms that it has the best stability to predict crop LAI when using variant remote sensors. In fact, there are continual changes of LAI values in the whole growing cycle of vegetation. In this study, the performance of VIUPD shows that it could be consider as dependable predictor in the estimation of vegetation LAI.

4. 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 two 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 0.8916-0.9158 and the RMSE of 0.21-0.24, which reaffirms that VIUPD is comparatively sensor independent. Other three SIs show a worse prediction accuracy and stability according to the different resampling sensors data. And then the consistence of VIUPD was to test between TM and Hyperion remote sensors. It shows that it has great consistence based on the simulated sensors we selected.

In conclusion, when predicting crop LAI or other vegetation biochemical parameters by SI method, the stability and consistency of LAI estimation is equally important to the estimation accuracy. And for one certain remote sensor, the selection of SI has to consider the physical significance of SI and the influence factor of sensor itself, with the purpose of increasing the prediction accuracy and stability. 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.

ACKNOWLEDGEMENTS

The work was funded under the National Natural Science Foundation of China (41371362/41371359/41201348) and the National Science and Technology Support Program of China (2012BAH29B03).

REFERENCES

- [1] Q. Tong, B. Zhang and L. Zheng, [Hyperspectral Remote Sensing: Principle, Technology and Application], Higher Education Publishers, Beijing, 365-377 (2006).
- [2] J. Borzuchowski and K. Schulz, "Retrieval of Leaf Area Index (LAI) and Soil Water Content (WC) Using Hyperspectral Remote Sensing under Controlled Glass House Conditions for Spring Barley and Sugar Beet," *Remote Sens.* 2(7), 1702-1721 (2010)
- [3] C. Wu, Z. Niu, J. Wang, S. Gao and W. Huang, "Predicting leaf area index in wheat using angular vegetation indices derived from in situ canopy measurements," *Can. J. Remote Sens.* 36(4), 301-312 (2010)
- [4] P. Gong, R. Pu, G. S. Biging and M. R. Larrieu, "Estimation of forest leaf area index using vegetation indices derived from Hyperion hyperspectral data," *IEEE. Trans. Geosci. Remote Sen.* 41(6), 1355-1362 (2003)
- [5] C. Wu, X. Han, Z. Niu and J. Dong, "An evaluation of EO-1 hyperspectral Hyperion data for chlorophyll content and leaf area index estimation," *Int. J. Remote Sens.* 31(4), 1079-1086 (2010)
- [6] C. D. Elvidge and Z. Chen, "Comparison of broad-band and narrow-band red and near-infrared vegetation indices," *Remote Sens. Environ.* 54(1), 38-48 (1995)
- [7] N. H. Broge and E. Leblanc, "Comparing prediction power and stability of broadband and hyperspectral vegetation indices for estimation of green leaf area index and canopy chlorophyll density," *Remote Sens. Environ.* 76(2), 156-172 (2001)
- [8] J. Pisek and J. M. Chen, "Comparison and validation of MODIS and VEGETATION global LAI products over four BigFoot sites in North America," *Remote Sens. Environ.* 109(1), 81-94 (2007)
- [9] J. L. Hatfield and J. H. Prueger, "Value of Using Different Vegetative Indices to Quantify Agricultural Crop Characteristics at Different Growth Stages under Varying Management Practices," *Remote Sens.* 2(2), 562-578 (2010)
- [10] N. J. Breda, "Ground-based measurements of leaf area index: a review of methods, instruments and current controversies," *J. Exp. Bot.* 54(392), 2403-2417 (2003)
- [11] H. Changping, L. Bo, Z. Xia and T. Qingxi, "Study on Band Selection and Optimal Spectral Resolution for Prediction of Cu Contamination in Soils," *Remote Sens. Techn. Appl.* 3), 353-357 (2010)
- [12] L. Zhang, S. Furumi, K. Muramatsu, N. Fujiwara, M. Daigo and L. Zhang, "Sensor-independent analysis method for hyperspectral data based on the pattern decomposition method," *Int. J. Remote Sens.* 27(21), 4899-4910 (2006)
- [13] L. Zhang, Y. Mitsushita, S. Furumi, K. Muramatsu, N. Fujiwara, M. Daigo and L. Zhang, "Universality of modified pattern decomposition method for satellite sensors," in *Asia GIS Conference Publications*, Wuhan

University, China (2003).

- [14] I. Jonckheere, S. Fleck, K. Nackaerts, B. Muys, P. Coppin, M. Weiss and F. Baret, "Review of methods for in situ leaf area index determination," *Agricultural and Forest Meteorology* 121(1-2), 19-35 (2004)
- [15] A. Bannari, D. Morin, F. Bonn and A. Huete, "A review of vegetation indices," *Remote Sens. Rev.* 13(1-2), 95-120 (1995)
- [16] A. L. Nguy-Robertson, "The mathematical identity of two vegetation indices: MCARI2 and MTVI2," *Int. J. Remote Sens.* 34(21), 7504-7507 (2013)