

COMPARISON OF ACCURACY AND STABILITY OF ESTIMATING WINTER WHEAT CHLOROPHYLL CONTENT BASED ON SPECTRAL INDICES

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ABSTRACT

Spectral index method was widely applied to the inversion of crop chlorophyll content. In this study, PSR3500 spectrometer and SPAD-502 chlorophyll fluorometer were used to acquire the spectrum and relative chlorophyll content (SPAD value) of winter wheat leaves on May 2nd 2013 when it was at the jointing stage of winter wheat. Then the measured spectra were resampled to simulated TM multispectral data and Hyperion hyperspectral data respectively, using the Gaussian spectral response function. We chose four typical spectral indices including Normalized Difference Vegetation Index (NDVI), Triangle Vegetation Index (TVI), the ratio of Modified Transformed Chlorophyll Absorption Ratio Index (MCARI) to Optimized Soil Adjusted Vegetation Index (OSAVI) (MCARI/OSAVI) and Vegetation Index Based on Universal Pattern Decomposition Method (VIUPD), which were constructed with the feature bands sensitive to the vegetation chlorophyll. After calculating these spectral indices based on the resampling TM and Hyperion data, the regression equation between spectral indices and chlorophyll content was established. For TM, the result indicates that VIUPD has the best correlation with chlorophyll ($R^2=0.8197$) followed by NDVI ($R^2=0.7918$), while MCARI/OSAVI and TVI also show a good correlation with R^2 higher than 0.5. For the simulated Hyperion data, VIUPD again ranks first with $R^2=0.8171$, followed by MCARI/OSAVI ($R^2=0.6586$), while NDVI and TVI show very low values with R^2 lesser than 0.2. It is demonstrated that VIUPD has the best accuracy and stability to estimate chlorophyll of winter wheat whether

using simulated TM data or Hyperion data, which reaffirms that VIUPD is comparatively sensor independent.

Index Terms—spectral resampling; spectral indices; inversion of chlorophyll content; regression analysis; inversion accuracy and stability

1. INTRODUCTION

Chlorophyll is a critical important pigment in the process of vegetation photosynthesis, which indicates the growth of plants, the conditions of physiological stress, the capacity of carbon sequestration and the efficiency of nitrogen usage [1][2]. Therefore, timely monitoring crop chlorophyll content by using remote sensing technology plays an important role in estimating the yield and monitoring crop pests [1].

The methods of inverting chlorophyll mainly includes multiple regression method and the physical model method. Owing to the disadvantages of the physical models, for example the complex algorithm based on so many factors, difficulties in acquisition of input parameters, the inversion accuracy of physical model method is thus restricted [1]. In previous studies, the spectral indices method has been widely used due to its simple and quick retrieval characteristics. Spectral indices establishment refer to certain physical characteristics, as well as eliminate the spectrum of environmental background such as the non-vegetation target like soil and water. Therefore, we can choose the spectral indices which have high sensitivity to

chlorophyll to estimate the crop leaf chlorophyll content[1].

Pisek and Chen (2007) pointed out that various spectral indices derived from broadband sensors are used with regard to their capacity to estimate biochemical parameters of vegetation, including LAI and chlorophyll content[2]. Sims and Gamon (2002) also used the empirical models method to predict chlorophyll content from band reflectance at 550nm and 700nm, where the absorption effect occurs due to higher chlorophyll content. Therefore, the spectral indices constructed with these bands have higher estimation accuracy[3]. Wu established the spectral indices containing red edge position 705nm and 750nm to estimate the chlorophyll of wheat reliably[4]. Previous studies have focused on band selection and spectral indices establishment in order to improve the accuracy of chlorophyll retrieval, but ignored the retrieval stability of spectral indices based on data from different sensors. Since the spectral responses of different sensors have a large difference[5], the same spectral index derived from different sensors has different accuracy and stability when estimating vegetation chlorophyll content. The purpose of this study is to investigate both accuracy and stability of spectral indices for estimating vegetation chlorophyll content based on simulated synchronous multi-spectral and hyperspectral data.

2. DATA AND METHODOLOGY

The study area was located at Xiao Tangshan agriculture experimental sites of ChangPing area in Beijing, China. PSR3500 spectrograph and SPAD-502 chlorophyll

fluorometer were used to get the spectrum and relative chlorophyll content (SPAD value) of winter wheat leaves on May 2nd 2013 when was just at the jointing stage of winter wheat. Then the measured spectra were respectively resampled to simulated TM multispectral data and Hyperion hyperspectral data using the Gaussian spectral response function [see Eq. (1)]

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

Where t is the distance from both ends to the center of each Gaussian function. μ is expected value and stands for the central wavelength of each function. σ is standard deviation used to calculate t . The band numbers after resampling is the numbers of Gaussian function. The spectral values after sampling are the integration of each Gaussian in interval $[\mu-t, \mu+t]$ [6].

This research chose four typical spectral indices including Normalized Difference Vegetation Index (NDVI), Triangle Vegetation Index (TVI), (Modified Transformed Chlorophyll Absorption Ratio Index) To (Optimized Soil Adjusted Vegetation Index) Ratio (MCARI/OSAVI) and Vegetation Index Based On Universal Pattern Decomposition Method (VIUPD), which were constructed with the feature bands sensitive to the vegetation chlorophyll[5][7][9]. After calculating these spectral indices based on the resampling TM and Hyperion data, the regression equation would be established between spectral indices and chlorophyll content. Table.1 and Table.2 shows the formulas of four spectral indices after resampling to TM and Hyperion.

Table.1 The formulas of four spectral indices after resampling to TM

Spectral index	Formulation
$NDVI_{TM}$	$NDVI_{TM} = (TM_4 - TM_3)/(TM_4 + TM_3)$
TVI_{TM}	$TVI = 0.5 * [120 * (TM_4 - TM_2) - 200 * (TM_3 - TM_2)]$
$MCARI / OSAVI_{TM}$	$MCARI / OSAVI_{TM} = \frac{\left[\left(\frac{TM_3 + TM_4}{2} - TM_3 \right) - 0.2 \times \left(\frac{TM_3 + TM_4}{2} - TM_2 \right) \right]}{(1 + 0.16)(TM_4 - TM_3)/(TM_4 + TM_3 + 0.16)}$

Table.2 The formulas of four spectral indices after resampling to Hyperion

Spectral index	Formulation
$NDVI_{Hyperion}$	$NDVI_{Hyperion} = (R_{750} - R_{705}) / (R_{750} + R_{705})$
$TVI_{Hyperion}$	$TVI_{Hyperion} = 0.5 * [120 * (R_{752} - (R_{548} + R_{559}) / 2) - 200 * (R_{671} - (R_{548} + R_{559}) / 2)]$
$MCARI / OSAVI_{Hyperion}$	$MCARI / OSAVI_{Hyperion} = \frac{[(R_{750} - R_{705}) - 0.2 * (R_{750} - R_{550})] * (R_{750} / R_{705})}{(1 + 0.16) * (R_{750} - R_{705}) / (R_{750} + R_{705} + 0.16)}$
$VIUPD_{Hyperion}$	$VIUPD = (C_v - 0.1C_s - C_4) / (C_w + C_v + C_s)$

3. RESULTS AND DISCUSSION

Due to the abnormal data existing among the sample data, so getting rid of some abnormal data is often forced to do when making regression analysis [10]. The figure 1 and figure 2 show the regression relationship between the four spectral indices and chlorophyll based on simulated TM data and Hyperion data. Figure 3 shows the comparison of inversion results based on simulated TM and Hyperion data. For TM, the result indicates that VIUPD has the best correlation with chlorophyll ($R^2=0.8197$) followed by NDVI ($R^2=0.7918$), while MCARI/OSAVI and TVI also show a good correlation with R^2 higher than 0.5. For the simulated Hyperion data, VIUPD with $R^2=0.8171$ again stand first followed by MCARI/OSAVI ($R^2=0.6586$), while NDVI and TVI show very low values with R^2 lesser than 0.2.

It is demonstrated that VIUPD has the best accuracy and stability to estimate chlorophyll of winter wheat whether based on resampling TM or Hyperion data, which reaffirms that VIUPD is comparatively sensor independent [5]. The chlorophyll estimation accuracy and stability of MCARI/OSAVI also works well depending on OSAVI which removes the influence of backgrounds [7]. Two broadband spectral indices NDVI and TVI are weak for chlorophyll estimation for Hyperspectral sensor Hyperion because of dependence on few bands and the strong influence of atmosphere, solar altitude, viewing angle of sensor, background and so on [9].

In conclusion, the stability and consistency of chlorophyll estimation is equally important to the estimation accuracy by spectral indices method.

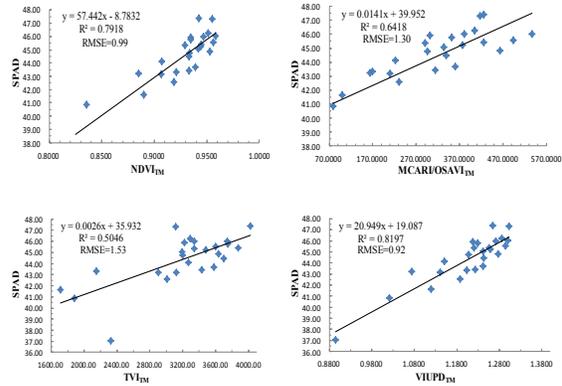


Fig. 1. The regression relationship between the four spectral indices and chlorophyll based on simulated TM data

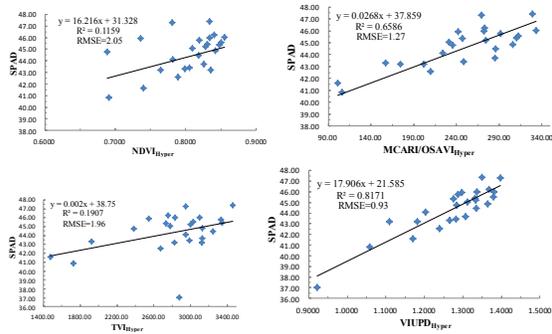


Fig. 2. The regression relationship between the four spectral indices and chlorophyll based on simulated Hyperion data

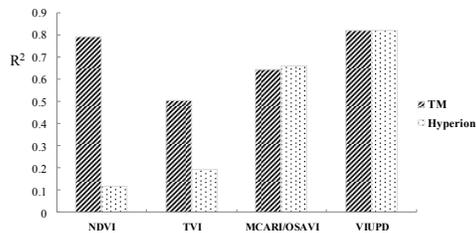


Fig.3. The comparison of inversion results based on simulated TM and Hyperion data

4. CONCLUSIONS

In conclusion, VIUPD introduced in the present study has the best effect to estimate winter wheat chlorophyll, which illustrates its potential ability in the area of estimating vegetation biochemical parameters. The chlorophyll estimation accuracy and stability of MCARI/OSAVI also works well, partly because OSAVI could reduce the influence of backgrounds. Two broadband spectral indices NDVI and TVI are weak for the chlorophyll estimation of simulated Hyperion data mainly because of their dependence on few bands and the strong influence of atmosphere, solar altitude, viewing angle of sensor, background and so on. In conclusion, the stability and consistency of chlorophyll estimation is equally important to the estimation accuracy by spectral index method.

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