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Full Length Research Paper

A study on hyperspectral estimating models of tobacco Leaf Area Index

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Leaf Area Index (LAI) is an important biophysical parameter and is a critical variable in many ecology models, productivity models, and carbon circulation studies. To assess and compare various hyperspectral models in terms of their prediction power of tobacco LAI, tobacco canopy hyperspectral reflectance data of the root extending stage, fast growing stage, and mature stage in different water-nitrogen conditions were collected with a FieldSpec HandHeld spectroradiometer. Based on the pot experiment data, an evaluation of tobacco LAI retrieval methods was conducted using four vegetation indices, principal component analysis (PCA), and neural network (NN) methods. The estimated effects of the three methods were then compared. Results indicated that all three methods have ideal effects on LAI estimation. Determination coefficients (R^2) of the validated models of vegetation indices, PCA, and NN were (0.768 ~ 0.852), 0.938, 0.889, respectively. The PCA and NN methods show higher precision. The stability of the PCA validated model is the best because its Root Mean Square Error (RMSE) of 0.172 is smaller than those of the vegetation indices (0.237 ~ 0.322) and NN (0.195). As a whole, the PCA and NN methods could improve the retrieval precision and were prior selection for LAI estimation.

Key words: Hyperspectral, flue-cured tobacco, LAI, vegetation Indices, principal component analysis, neural network.

INTRODUCTION

Leaf Area Index (LAI) is a critical parameter for estimating biomass and for quantitatively analyzing the energy exchange characteristics of terrestrial ecosystems (Broge and Mortensen, 2002). Estimating crop LAI is particularly significant for crop-growing conditions, pest and disease monitoring, yield estimation, and field management. There is a wide range of effective methods for the small-scale measurement of LAI. However, only the use of remote sensing technology is feasible for predicting LAI on the large or even global scale (Fassnacht et al., 1997). Previous studies found that green crop spectral reflectance shares an important relationship with LAI (Guan et al., 2002; Hu et al., 2004; Gupta et al., 2006). With the development of hyperspectral technology, more and more researchers have begun to take advantage of hyperspectral remote sensing methods to retrieve LAI (Broge et al., 2001; Imanishi et al., 2004; Jiang et al., 2005). Different scholars from various perspectives and methods have studied the remote sensing problem of LAI inversion at different scales and vegetation types, and many studies are dedicated to building a radiative transfer model to improve the accuracy of LAI inversion (Qi et al., 1995).

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Moderate-resolution imaging spectroradiometer (MODIS) LAI products based on the three-dimensional radiative transfer model have become a research focus, an application, and an important and convenient data source (Myneni et al., 1997; Wythers et al., 2003). However, the application of a physical model is limited because of the addition of parameters, algorithm complexity, and slower computations. Other works on spectral reflectance and vegetation index aim to improve the accuracy of LAI inversion (Casanova et al., 1998; Hansen et al., 2003; Hung et al., 2006). While the accuracy of a large number of statistical models between spectral vegetation indices and LAI established based on hyperspectral remote sensing technology has been greatly improved, the accuracy and universality of the vegetation index method remain difficult to guarantee.

Many studies have shown that the relationship between vegetative bio-physico-chemical parameters and spectral reflectance is basically nonlinear (Kokaly et al., 1999; Curran et al., 2001). Neural networks (NN) have an unparalleled advantage in fitting nonlinear problems. Thus, some researchers have begun to introduce neural networks to high-spectral data analysis to improve the accuracy of the inversion of vegetative physiological parameters (Delfrate and Wang, 2001; Bacour et al., 2006; Song et al., 2006). Hyperspectral data can provide a wealth of detailed spectral information, but large volume of data and redundant information pose a challenge for data processing.

The principal component analysis (PCA) method, on the other hand, shows better data compression, reduces the amount of data dimension features, and can make full use of data to achieve complementary advantages between the different spectral bands and improve the accuracy of estimates (Lelong et al., 1998; Gong et al., 2002; Yang et al., 2008). The current remote sensing technology is focused mainly on rice, wheat, corn and other major food crops (Asrar et al., 1985; Shibayama and Akiyama, 1989; Goel et al., 2003), but less on tobacco.

As an important economic crop, tobacco is planted in several provinces in China and its planting area and yield are very large. Moreover, with its broad leaves and small planting density, tobacco is quite different from rice, wheat, and other graminaceous plants that feature narrow leaves and small planting densities. Chaurasia et al. (2006) reported an estimate of tobacco LAI with IRS-ID LISS-III data. Li et al. (2007) systematically analyzed the hyperspectral characteristics of different tobacco types, flue-cured tobacco varieties, nitrogen, phosphorus, and potassium application rate treatments. They also established a prediction model for tobacco LAI and above-ground biomass via a multiple stepwise regression method. However, studies on the spectral characteristics of tobacco leaf area under different water and nitrogen stress are relatively rare.

This paper introduces PCA and NN technology, estimates tobacco LAI from hyperspectral data, and compares several regression models constructed from different vegetation indices to investigate the accuracy of different models in retrieving change in tobacco leaf areas.

MATERIALS AND METHODS

Experimental design

The experiment was carried out on a farm at Henan Agricultural University in Zhengzhou City, China (34°30 N, 113°24 E) in 2009. The basic properties of soil were as follows: middle level fertility, 13 g kg^{-1} organic matter, 0.87 g kg^{-1} total nitrogen, 69.74 mg kg^{-1} alkali hydrolysable N, 13.75 mg kg^{-1} available phosphorus, 113.00 mg kg^{-1} available potassium, pH 7.92, and 24.2% field moisture capacity. A Pot experiment was employed. Flue-cured tobacco varieties used for this experiment were K326 and YUN 85.

Nitrogen treatments

Each pot was filled with 20 kg soil taken from the local field and planted with one tobacco plant. Three nitrogen levels were applied: N0 meant no nitrogen was applied to the pot, N1 meant 3 g nitrogen was applied to each pot, and N2 meant 6 g nitrogen was applied to each pot. In addition, 4.5 g P_2O_5 and 9 g K_2O were applied to each pot.

Moisture treatments

Three moisture levels were employed for the experiments: M0 meant 45% of field moisture capacity was used, M1 meant 65% of field moisture capacity was used, and M3 meant 85% of field moisture capacity was used. Each treatment setting was repeated three times in a randomized block arrangement. The fertilizers used were NH_4NO_3, K_2SO_4, and Ca $(H_2PO_4)_2H_2O$. All P_2O_5, 70%N and 70%K_2O were applied to the plants before transplanting. The top-dressing used consisted of 30%N and 30%K_2O, applied 15 and 30 d after transplanting.

The distance between rows and plants was 120 and 60 cm, respectively. Transplanting was conducted on May 15. Cultivation was dependent on normal field management. The weighing method was employed to control the soil moisture content of each treatment. Each moisture treatment began from the root extending period and continued until the end of the mature period.

Canopy spectral data acquisition

To obtain spectral data, an America Analytical Spectral Device (ASD) FieldSpec HandHeld was used, which provided spectral coverage from 350 nm to 1050 nm at sampling intervals of 1.4 nm and a spectral resolution of 3nm. Samples were selected from healthy leaves at 35, 55, and 80 d after transplanting. For each treatment, three plants that grew consistently and reflected fertilizer conditions were selected. Canopy spectra reflectance was measured between 10:00 and 14:00 h: at these hours, the sky was clear. While measuring, the sensor probe was held downward vertically, away from the canopy top, and at a vertical height of 1 m.

The spectrometer FOV was 25°. Whiteboard calibrations were performed before each measurement. Each tobacco plant was measured thrice from the top and 10 sets of data were recorded for each measurement. The last data collected were considered as the

Table 1. Regression models based upon vegetation indices against LAI and its validation.

Vegetation indices	Model calibration	(n = 132)		Model validation	(n = 30)
	Regression model	R^2	RMSE	R^2	RMSE
RVI	$y = 0.011x^{1.760}$	0.796	0.251	0.768	0.322
NDVI	$y = 3.424x^{8.061}$	0.813	0.241	0.798	0.281
MSAVI	$y = 0.052e^{3.898x}$	0.852	0.217	0.849	0.263
MTVI2	$y = 2.911x-1.193$	0.878	0.202	0.852	0.237

average spectral reflectance values of the samples.

Tobacco leaf area measurement

After canopy spectral measurements, tobacco leaf areas were acquired by sampling three tobacco plants corresponding to the location where spectrum was collected. The leaves from all the plants were collected. Tobacco leaf area = length × width × 0.6345 (Liu, 2003).

Vegetation indices models

Vegetation indices have emerged as important tools in the monitoring, mapping, and resources management of the Earth' terrestrial vegetation. They are radiometric measures of the amount, structure and condition of vegetation, which serve as useful indicators of seasonal and inter-annual variations in vegetation. This paper chooses four vegetation indices commonly used in the inversion of vegetation LAI.

Normalized difference vegetation index (NDVI) and Ratio vegetation Index (RVI) are most commonly used in the inversion models of many physiological parameters (Rouse et al., 1974; Deering et al., 1975), while Modified soil -adjusted vegetation index (MSAVI) and Modified second triangular vegetation index (MTVI2) are vegetation indices constructed based fully on considerations of the impact of soil or other environmental background factors (Qi et al., 1994; Haboudane et al., 2004).

To facilitate comparison, all vegetation indices were built using 800 and 670 nm band spectral reflectance measurements.

Principal component analysis

PCA is a dimension reduction technique that uses correlated attributes, or variables, and identifies orthogonal linear recombination of the attributes that summarize the principal sources of variability in the data. A correlation matrix involving variables selected was used as an input for analysis in lieu of a covariance matrix, resulting in normalized PCA. There are as many PCs as variables included in the analysis. Generally, the first few components explain most of the total variance in the data set.

In the present study, PCs with eigenvalues 1 were selected as new variables (Wang et al., 2009). Bands included in vegetation indices are usually limited, PCA have a better effect which can make use of complementary advantages among different spectral bands (Chaurasia and Dadhwal, 2004; Ray et al., 2006; Chen et al., 2009).

Back propagation neural networks

Artificial neural network is a cutting-edge field that developed rapidly around the world from the mid and late 80s of the 20th century, Due to its good predictability and practicality, it has been widely used in various fields, especially in remote sensing image automatic classification and quantitative analysis (Diane et al., 1995; Karkee et al., 2009; Li et al., 2009). As the back propagation (BP) neural network features parallel processing, nonlinearity, fault-tolerance, adaptive and self -learning features, it has incomparable superiority in data fitting and simulation.

In this paper, using hyperspectral reflectance as the input vector, NN are employed to predict the tobacco LAI from spectral reflectance changes. A BP neural network analysis in MATLAB 7.0 was carried out using Neural Network Toolbox.

RESULTS

The hyperspectral vegetation index estimation of LAI

Table 1 lists the regression models and verified results of the vegetation indices with tobacco LAI. With coefficients of determination (R^2) and Root Mean Square Error (RMSE) as the evaluation indices, the best-fitting equation of the vegetation indices with tobacco LAI is found to be the exponential model, except for the index MTVI2, whose best regression model is linear. By comparison, the R^2 of the regression model based on MTVI2 is found to be significantly higher than that of RVI. Inversion accuracy values of regression models built by other vegetation indices are located in-between.

MTVI2 and MSAVI could remove the influence of soil and atmosphere noise. In addition, the measured and predicted data of the two vegetation indices agree very well with each other, thus significantly improving the inversion accuracy. Overall, the accuracy of the regression models established by the improved vegetation indices is slightly better than those of RVI and NDVI. Figure 1 shows the relationships between the measured tobacco LAI data and the predicted data of regression models built from the four vegetation indices. All the values for tobacco LAI inversion accuracy from different vegetation indices are different, but they all return satisfactory results.

The PCA estimation of LAI hyperspectral data

This paper uses the hyperspectral reflectance data of 16 visible and near-infrared center wavelengths of the MODIS sensor within 1050 nm, to test the partial correlation coefficients of the 16 variables, a test value of

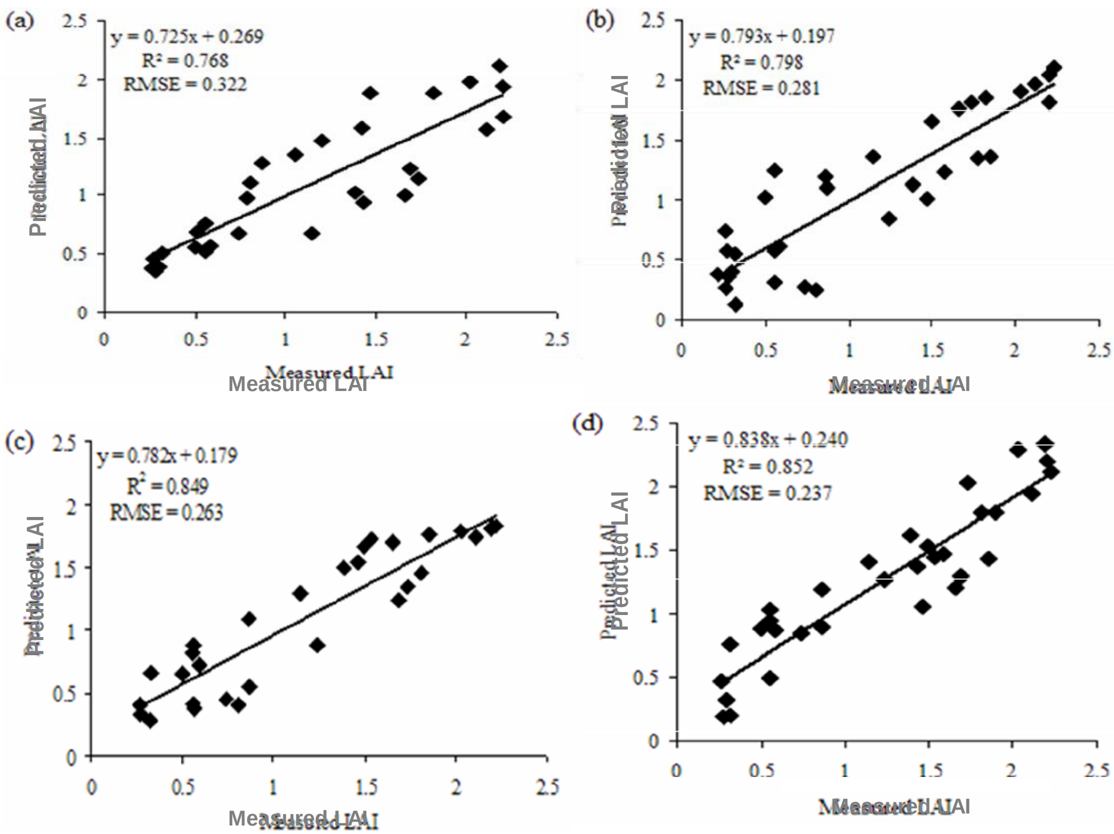

Figure 1. Validated model for LAI estimation of vegetation indices: (a) RVI; (b) NDVI; (c) MSAVI and (d) MTVI2.

Table 2. Principal components of hyperspectral reflectance from PCA.

PC	Eigenvalue	Component loading (%)	Cumulative loading (%)
PC1	9.182	57.390	57.390
PC2	6.131	38.320	95.710

Kaiser-Meyer-Olkin (KMO) 0.797 was obtained. Thus, the original 16 variables are suitable for factor analysis. Data processing results show that the 10 wavelengths within 412 ~ 678nm have higher loads in the first factor. The first factor mainly explains the information of the 10 wavelengths, all of which are in the visible light range. As such, the first factor is interpreted as the visible light factor. The remaining six wavelengths have higher loads in the second factor, and similarly, the second factor can be interpreted as the near-infrared factor.

As can be seen from Table 2, the two principal components retained 95.71% of the information of the original 16 wavelengths, and very little information was lost. Consequently, the two principal components can replace the original 16 variables. Using these two principal components to estimate the tobacco LAI, the results can be written as:

$$Y= 0.407f_1+0.285f_2+1.166 \quad R^2 = 0.910 \quad RMSE = 0.176, \qquad (1)$$

Where Y represents the LAI, and f1 and f2 are the visible and near-infrared factors obtained from the results of PCA analysis, respectively. The visible and near-infrared principal component factors derived from the principal component transform the hyperspectral reflectance data. 132 sample points were randomly selected to establish the estimation model of LAI, and 30 samples were used to verify the model accuracy. Good results were achieved, as shown in formula 1 and Figure 2. The R^2 of the estimation and verification models of LAI are 0.910 and 0.938, respectively, and the corresponding RMSE of the two models are 0.176 and 0.172, respectively. Therefore, the visible light and near- infrared factors obtained from PCA analysis can reflect the changes of LAI very well and can make accurate estimates of LAI.

Neural network estimation of LAI

In this paper, we employed the BP neural network

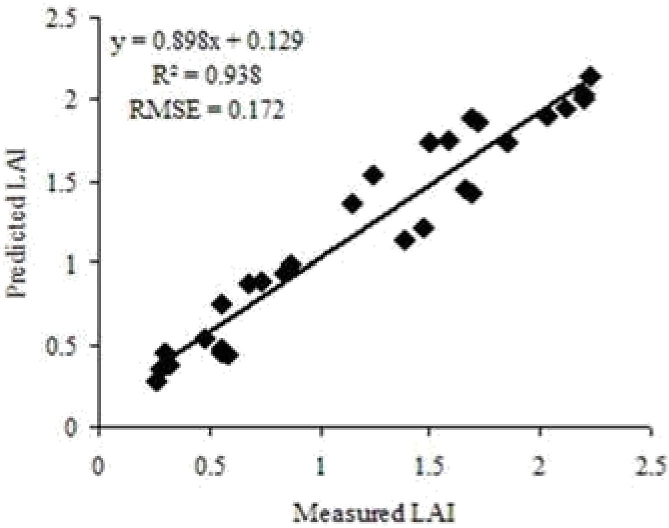

Figure 2. Relationship between measured LAI and simulated LAI by PCA model.

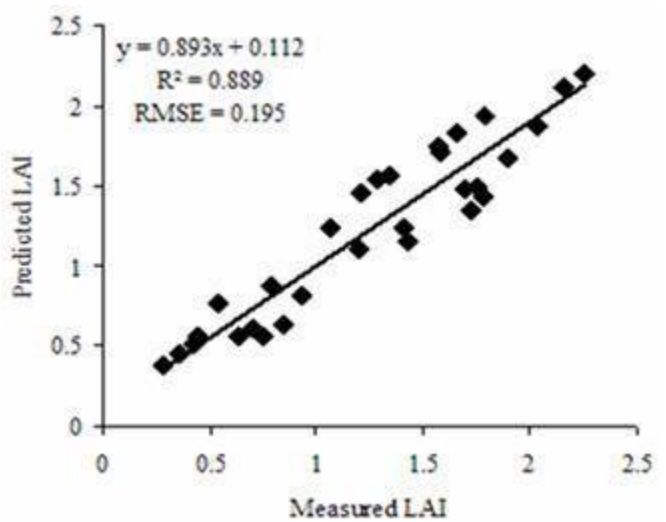

Figure 3. Relationship between measured LAI and simulated LAI by BP-NN model.

algorithm. The network has three layers: input layer, hidden layer, and output layer. The input layer has 16 input variables, specifically, the 16 variables obtained from the spectral reflectance of visible and near-infrared center wavelengths of the MODIS sensor within 1050nm. The transfer functions of the hidden layer and output layers are designated as "tansig" and "purelin," respectively. The output layer exports LAI, the training function is Trainlm, the network error goal is 0.001, and the training iterations is 1000. Through multiple authentication, better LAI estimation results are obtained when the number of hidden layer neurons is 7. 132 sample points were randomly selected to train BP network, and 30 samples were used to verify the network training result, the results are shown in Figure 3.

The R^2 and RMSE of fitting between the measured LAI data and the NN simulated data were 0.889 and 0.195, respectively, indicating that the measured and simulated tobacco LAI values have good consistency.

Comparison of the estimated LAI results from the three methods

From the comparison between Figures 1 to 3 and Table 3, it can be seen that the four kinds of vegetation index, PCA, and NN methods all achieved good results in estimating tobacco LAI. The determination coefficient of the estimation model of PCA reached 0.910, which is significantly higher than those of the vegetation indices method. The R^2 of the validation models of the PCA and NN methods were 0.938 and 0.889, respectively, which are again better than those of the vegetation indices method. The R^2 of the validation model of NDVI and RVI were 0.798 and 0.768, respectively.

The RMSE of the PCA, NN, NDVI and RVI methods were 0.172, 0.195, 0.322 and 0.281, respectively. This indicates that the validation model accuracy of the PCA and NN methods is much better than those of the vegetation indices method. Compared with NDVI and RVI, the simulation accuracy of MSAVI and MTVI2 did increased, but it is still not as good as those of the PCA and NN methods, their inversion accuracy is simply in the middle level. From Figures 1 to 3, the same conclusions can be drawn. In Figure 1, the distribution of the points is dispersed, while the points in Figures 2 and 3 are relatively densely distributed near the 1:1 diagonal. In fact, the simulated LAI and measured values are more or less the same. Overall, the PCA and NN methods can obtain more stable and accurate LAI estimation results.

DISCUSSION

The measured tobacco hyperspectral and LAI data of different water and nitrogen treatments were analyzed under the conditions of the pot experiment, and the estimation effects of the vegetation indices, PCA, and NN methods were compared. The vegetation indices method generally uses information from only a few wavelengths, it is difficult to guarantee its model stability. The PCA and NN methods can fully exploit the hyperspectral information of each band to achieve complementary information between the various bands, thus significantly reducing random disturbances brought about by small numbers of bands. Using the hyperspectral data of many bands also results in a more reliable and universal estimation of tobacco LAI.

The two main components transformed by PCA are interpreted as the visible light factor and near-infrared

Table 3. Validation models comparison of three methods.

Methods	R^2	RMSE
RVI	0.768	0.322
NDVI	0.798	0.281
MSAVI	0.849	0.263
MTVI2	0.852	0.237
PCA	0.938	0.172
NN	0.889	0.195

factor. These two factors include 95.71% of the information of hyperspectral data. The PCA method has an ideal effect in LAI estimation (estimate model 0.910) and its validation model's accuracy is significantly higher than those of the vegetation indices and NN methods. The application of neural networks in processing hyperspectral data is a relatively new field and remains exploratory at best. The input layer and hidden layer numbers, as well as the best combination between the input and hidden layers and learning rate, must be carefully selected because all of those will have great impact on the processing results of hyperspectral data. Its coherent predicted and measured values show its good potential for future applications.

As for the band combination, at present, no specific rules can be followed.

In this article, only the hyperspectral data of the MODIS of 16 bands which could be found before the 1050 nm wavelength were used, other bands have not yet been analyzed. With the PCA and NN methods, the effect of integrating the hyperspectral data of the bands after the 1050 nm wavelength (for example, to 2500 nm or so) to estimate the tobacco LAI requires further study.

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