Mapping Crop Leaf Area Index from Multi-spectral Imagery Onboard an Unmanned Aerial Vehicle

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***Abstract*—Leaf area index (LAI) is a significant biophysical parameter used in many agronomic and ecological models. In comparison with satellite remote sensing, unmanned aerial vehicles(UAV) technology can obtain imagery with high spatial resolution for better accuracy of LAI estimation. This study conducted global sensitivity of input variables in PROSAIL model by the extended Fourier amplitude sensitivity test (EFAST) method and determined the most sensitive bands and vegetation indices (VIs) to LAI. Estimation accuracy of five input variable combinations in cost-functions was compared. Results of global sensitivity analysis show that green and red band are sensitive to LAI, and the correlation coefficient between measured LAI and estimated LAI from combination of these two bands as input variables in cost-functions is 0.85. For VIs, the most sensitive input variables are LAI, average leaf angle(ALA) and chlorophyll content(Chl). VIs of NDVI, RVI and MSR are sensitive to LAI with corresponding total sensitivity of 0.80, 0.69 and 0.72 respectively. The correlation coefficient between measured LAI and estimated LAI from VIs is over 0.75, indicating that it may be an alternative way for LAI inversion in PROSAIL model through LUT method.**

***Keywords*—unmanned aerial vehicle, leaf area index, PROSAIL model, crops, vegetation index, winter wheat, global sensitivity analysis**

I. INTRODUCTION

Leaf area index (LAI) is considered to be a significant biophysical variable of ecosystem processes[1], used in numerous hydrological, agricultural, meteorological and ecological models[2]. Current technology and management techniques such as reasonable LAI estimation are important to quantify crop variability[3] and monitor crop growth in terms of precision farming. Manual methods for LAI measurement are time consuming and destructive, while remote sensing has shown the great potential for quickness and timeliness. Satellite-derived information is extensively used in land cover and biome type mapping, estimation and monitoring of vegetation biophysical and biochemical variables, such as LAI, chlorophyll content and chlorophyll fluorescence. However, owing to the high cost of data acquisition, coarse spatial resolution and dependence on weather condition, the application of satellite-derived information for precision farming is limited[4]. Unmanned aerial vehicle (UAV), as a low altitude remote sensing platform, is able to estimate LAI in agronomic research at large scales[5], thanks to the higher spatial and temporal resolution than satellites[6].

Statistical and physical methods are two main approaches for LAI estimation from satellite-derived remote sensing images[7]. Statistical methods are based on regression models between spectral vegetation indices (VIs) and measured LAI *in situ*, and the other is the inversion of input variables in the radiative transfer models(RTMs). PROSAIL model is one of the RTMs[8], which combines the PROSPECT leaf model and the SAILH canopy bidirectional reflectance model[9]. It is the most used due to the general robustness and ease of usage.

Because of complexity and magnanimity of earth surface, properties and principles observed at the scale of remote sensing by satellites may not be applicable at the scale of UAV remote sensing[10], so it is necessary to test the applicability of existing methods. Most of studies focus on global sensitivity analysis of bands to input variables in the PROSAIL model; however, little attention has been paid to the global sensitivity of VIs to model input variables. In addition, most of studies utilize single bands instead of VIs as input variables in cost-functions when using look-up-table(LUT) method for LAI inversion.

The objectives of this study are twofold: (1) to conduct global sensitivity analysis of bands and VIs to input variables in PROSAIL model, and determine the most sensitive ones for LAI inversion; and (2) to compare the accuracy of LAI estimation from different input variables as the constraints in cost-functions when using LUT approach.

II. MATERIAL AND METHODS

A. Study area overview

The study site is located at Yucheng Trial Station of Chinese Academic of Science (36°49'N,116°34'E), west Shandong Province in China. The regional climate is categorized as a warm temperate and semi-humid monsoon climate zone with annual mean temperature of 13.1℃ and average annual precipitation of 593.2 mm, mainly from July to September. Winter wheat was planted in the field.

Due to different nutrient (nitrogen, phosphorus and potassium) and water treatment among fields (Fig. 1), LAI measured *in situ* (Fig. 2), NDVI value based on UAV remote sensing images in the study area were relatively different, indicating significant spatial heterogeneity of crop growth. Therefore, the study area was feasible for LAI estimation of winter wheat from UAV remote sensing imagery[9].

B. Data sources and processing

In this field experiment, a Swiss SenseFly eBee Ag agricultural fixed wing UAV served as the aerial carrier platform to conduct sensor management, equipped with a Multi-SPEC 4C camera which has four separate 1.2MP sensors including four band data: green band (550nm), red band (660nm), red-edge band (735nm) and near infrared red band (NIR) (790nm).

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Two UAV flight tests were conducted on 11th of May, 2016 and 22nd of April, 2017 when it was the filling stage and the heading stage of winter wheat in each year respectively. To rule out the effect of weather, tests were performed at cloudless noon. Before each flight, whiteboard data was collected for later radiation correction. Radiation correction, image splice and orthography of UAV remote sensing images were conducted by Pix4D Mapper Pro 3.1.22. Each flight test produced around 700 images of four bands totally over all experimental plots, with spatial resolution of approximately 0.10m. The projection mode for data processing was UTM/WGS84. LAI value *in situ* was collected by destructive method within three days of the flight test, and determined in laboratory.

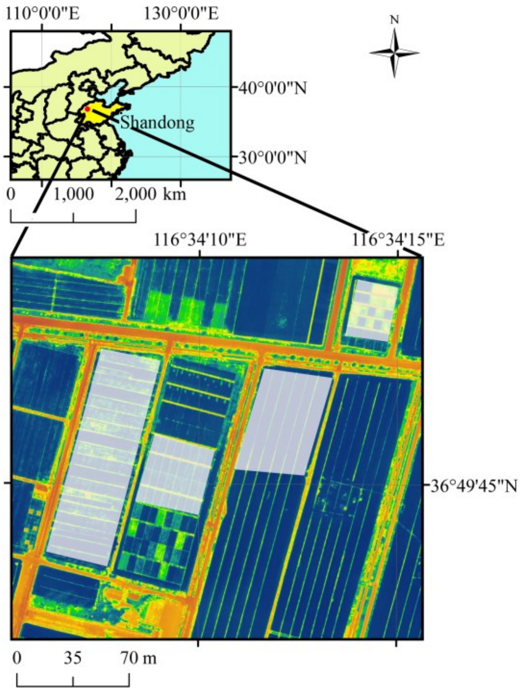

Fig.1 Location of study area and experimental field

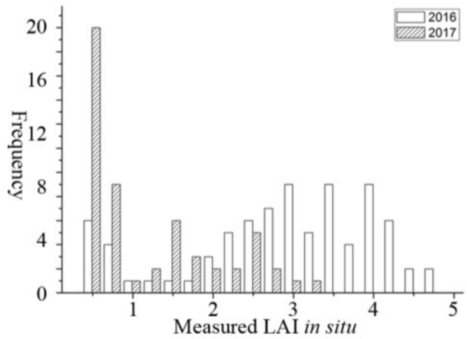

Fig. 2 Frequency distribution of LAI value *in situ*

C. *Method*

The PROSAIL model is commonly applied to describe the reflection characteristics of a uniform canopy[11] derived from the combination of PROSPECT blade model and the SAILH canopy structure model. The PROSPECT model simulates the optical properties of leaves, from 400nm to 2500nm, including four parameters: leaf structure index (N), chlorophyll content (Chl), leaf water mass per area (LMA) and blade equivalent thickness (EWT). The SAILH model is a radiative transfer model on the canopy scale. In SAILH model, vegetation is treated as a mixed medium, with the assumption that the blade azimuth distribution is uniform. The absorption and scattering coefficients of arbitrary blade inclination distribution are calculated by using the obliquity distribution function as the weight, and the effects of blade size and shadow on the coefficients of absorption and scattering are taken into account. The SAIL model includes 8 input parameters: LAI, average leaf angle (ALA), soil reflectance (ρsoil), hot spot, solar zenith and azimuth, observational zenith and azimuth.

Sensitivity analysis is a qualitative or quantitative impact analysis of input variables on model outcome. The change of sensitive input variable value often causes significant variation of model outcome, whereas the insensitive ones do not. The global sensitivity analysis identifies the effect of each input variable and the interaction between them on the model outcome. This study performed the extended Fourier amplitude sensitivity test (EFAST) method to test global sensitivity analysis of the input variable in the PRPOSAIL model. Many studies have conducted global sensitivity analysis of single bands to input variables and have used several single bands as input variable of cost-functions in LUT method to inverse LAI; however, very few used VIs for that purpose.

In order to determine the optimal VI for LAI inversion of winter wheat, this study selected 12 commonly used VIs according to the wave band of the sensor (Table I).

TABLE I. COMMONLY USED VEGETATION INDICES AND FORMULAS

VIs	Abbr.	Formula
Enhanced Vegetation Index without the blue band	EVI2	2.5(NIR–R)/(NIR+2.4R+1)
Normalized Difference Vegetation Index	NDVI	(NIR–R)/(NIR+R)
Green Normalized Difference Vegetation Index	GNDVI	(NIR–G)/(NIR+G)
Ratio Vegetation Index	RVI	NIR/R
Modified Secondary Soil Adjusted Vegetation Index	MSAVI2	0.5{(2NIR+1)-sqrt[$(2NIR+1)^2$-8(NIR-R)]}
Optimized Soil Adjusted Vegetation Index	OSAVI	(NIR–R)/(NIR+R+0.16)
Soil Adjusted Vegetation Index	SAVI	(1+L) (NIR–R)/(NIR+R+L) (L=0.5)
Modified Chlorophyll Absorption Ratio Index	MCARI	1.5[2.5(NIR-R)-1.3(NIR-G)]/ sqrt[$(2NIR+1)^2$-6(NIR-5R)-0.5]
Modified Triangular Vegetation Index	MTVI1	1.2[1.2(NIR-G)-2.5(R-G)]
Modified Simple Ratio	MSR	(NIR/R-1)/sqrt(NIR/R+1)
Triangular Vegetation Index	TVI	0.5(120(NIR-G))-200(R-G)
Difference Vegetation Index	DVI	NIR-R

Note: G is green band, R is red band, NIR is near infrared red band

Since the underlying surface only included crops and soil, VIs value of each field block was calculated from the mean value of the total pixels. The linear regression analysis was carried out between the estimated LAI and measured LAI, and model was evaluated by the correlation coefficient(r), the root mean square error(RMSE) and the mean relative error(MRE).

$$\mathrm{RMSE}=\sqrt{\frac{\sum_{i=1}^{n}(Y_i-E_i)^2}{n}} \tag{1}$$

$$\mathrm{MRE}=\frac{1}{n}\sum_{i=1}^{n}\frac{|Y_i-E_i|}{Y_i} \tag{2}$$

Where, i represents the serial number of the sample. Y_i and E_i represent measured LAI and estimated LAI of the i th sample respectively.

LUT is commonly used in LAI inversion due to its simplicity and rapidity. As shown in Table II, value of input variables in PROSAIL model was set from the priority information, such as the LOPEX'93 database, related studies and the *in situ* measurements. Besides Chl and LAI, values of other input variables were set to constants. The numerical range of LAI value is 0.2 to 5, with step size value of 0.01; and the numerical range of Chl value is 20 to 70, with step size value of 1. LUT was sorted in terms of cost-functions as formula (3) and (4), and LAI was inversed by minimizing the value of cost-functions.

TABLE.II VALUE OF THE INPUT VARIABLES FOR THE PROSAIL MODEL TO GENERATE LUT

Variable	**Abbr.**	**Unit**	**Value**
Leaf structure parameter	N	Unitless	1.5
Leaf chlorophyll content	Chl	$\mu g \cdot cm^{-2}$	20-70 (step:1)
Leaf carotenoid content	caro	$\mu g \cdot cm^{-2}$	10
Brown pigment content	brown	arbitrary units	0
Blade equivalent thickness	EWT	cm	0.01
Leaf water mass per area	LMA	$g \cdot cm^{-2}$	0.005
Soil brightness parameter	psoil	Unitless	0.1
Leaf area index	LAI	$m^2 m^{-2}$	0.2-5 (step:0.01)
Hot-spot size parameter	hot spot	$m\,m^{-1}$	0.2
Solar zenith angle ()	-	degrees	20
Solar azimuth angle	-	degrees	185
View zenith angle	-	degrees	0
View azimuth angle	-	degrees	0
Average leaf angle	ALA	Deg	70

$$\chi_{RMSE}=\sqrt{\frac{1}{n}\sum_{i=1}^{n}(R_{measured}-R_{simulated})^2} \tag{3}$$

$$\chi_{RRMSE}=\sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(\frac{R_{measured}-R_{simulated}}{R_{measured}}\right)^2} \tag{4}$$

Where, $R_{measured}$ is the measured value from UAV imagery; $R_{simulated}$ is the simulated value calculated from the PROSAIL model, and n is the number of bands or VIs as input variables of cost-functions when using LUT method.

III. RESULTS AND DISCUSSIONS

A. Global sensitivity analysis of the single bands to input variables in PROSAIL model

Fig.3 is the scatter graph between four bands and the measured LAI. It displays the significant variation of band reflectance in field blocks, especially the red-edge band. Variation of band reflectance indicated differences in crop growth as a result of different growing seasons, climate and environmental condition. Table. III displays correlation coefficient between single bands and measured LAI. It shows the reflectance of green band and red band are positively correlated with measured LAI. The annual reflectance of red edge band in 2016 and 2017 is almost not correlated with LAI, while the total reflectivity of this band is positively correlated with LAI. However, the trend of NIR band is the opposite. The reason could be that the sensitivity of different bands to the change of measured LAI is distinguishing. Owing to highly instable reflectivity of the single bands, they aren't applicable for LAI estimation. Yue et.al pointed out that single band for extraction of crop information had obvious limitations. For example, the reflectance information of a single band is affected by atmospheric and surrounding environment easily, so it is difficult to obtain the true value [6].

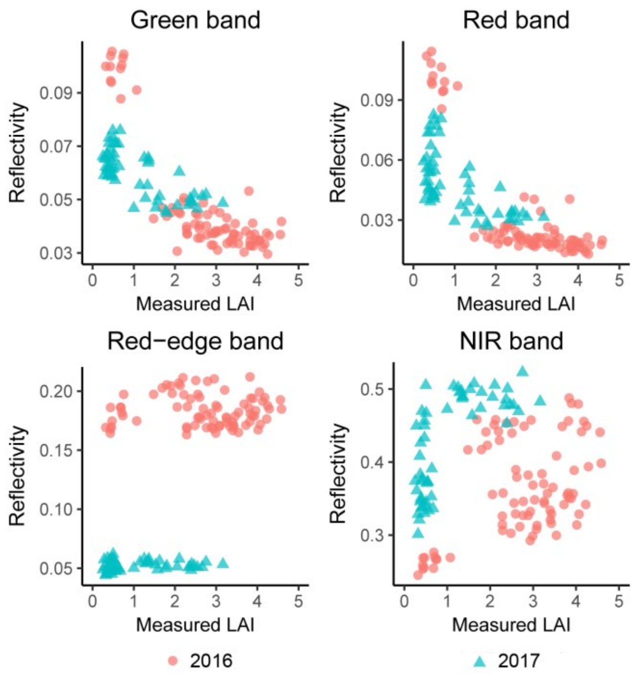

Fig.3 Scatter graph between the single band and measured LAI.

TABLE III. CORRELATION COEFFICIENT BETWEEN BANDS AND MEASURED LAI

Year	**Green**	**Red**	**Red-edge**	**NIR**
2016	-0.83	-0.81	-0.01	0.48
2017	-0.72	-0.63	0.17	0.70
total	-0.78	-0.75	0.62	0.12

EFAST method holds that the variance of model output is caused by input variables and their interactions. Value of the first-order sensitivity implies the direct contribution rate of input variables to the total variance of the model output. The total sensitivity includes the first-order sensitivity and the indirect contribution of interaction among input variables to the total variance of the model output. As displayed in Fig.4, results of the first-order sensitivity analysis show that the green band is sensitive to Chl, N and ALA. The red band is sensitive to LAI, Chl and ALA, while the red-edge band is sensitive to LAI and ALA, and NIR band is sensitive to LMA, ALA and LAI. Results of the total sensitivity analysis are similar to those of the first-order sensitivity. It shows that the green band is sensitive to Chl, N and ALA; The red band is sensitive to N, LAI, and Chl; The red-edge band is sensitive to LMA, ALA and Chl; and NIR band is sensitive to LMA, ALA and LAI. In this study, results of global sensitivity analysis are similar to other studies. For instance, Rasmus Houborg et al pointed out that green and red-edge bands are sensitive to the change of chlorophyll content [12] . Aleixandre Verger et al also held that the red-edge band is applicable for the estimation of chlorophyll content[13].

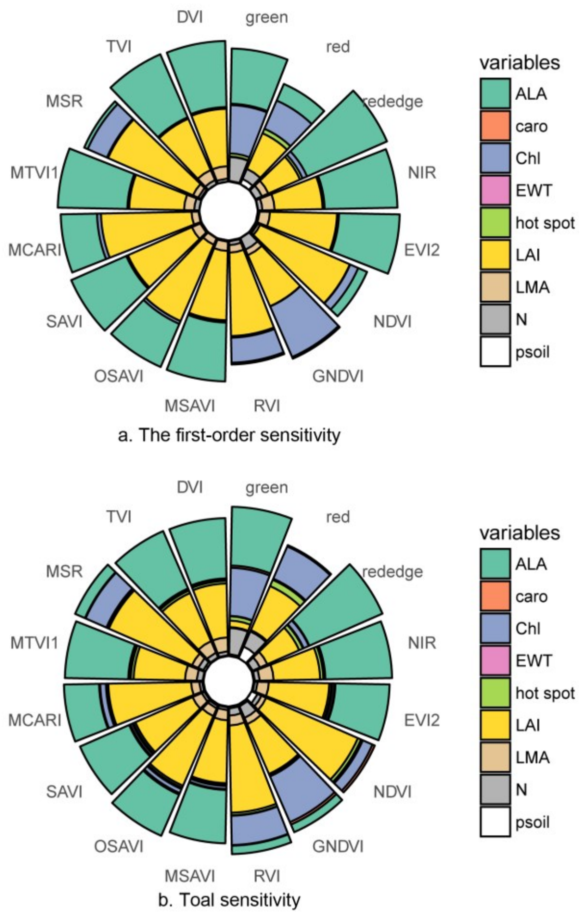

Fig.4 Global sensitivity Analysis of single band and VIs to input variables of PROSAIL model through EFAST method

B. Global sensitivity analysis of VIs to input variables in PROSAIL model

Since VIs can offset part of single band error from surrounding environment to obtain better vegetation information, this study used VIs as input variables of cost-functions. Based on the results of global sensitivity analysis of VIs to input variables of PROSAIL model(Part C), NDVI, RVI and MSR were selected. The correlation coefficient between these three VIs and measured LAI were shown in Table VI. Fig.5 is the scatter graph between VIs and measured LAI. Comparing the results of correlation analysis in 2016 and 2017, the correlation coefficient is more stable, less fluctuating and higher than those between bands and LAI(Part A). So it may be an alternative way to use VIs than single bands for LAI estimation.

Fig. 4 also displays the global sensitivity of VIs to input variables. The first-order and total sensitivity have the similar trend. Both of them suggest the most sensitive input variables for VIs are LAI, ALA and Chl, while the other input variables are weakly sensitive. Among the whole VIs, MSR, NDVI, RVI and GNDVI are not sensitive to ALA but sensitive to LAI and Chl. However, GNDVI is ruled out since its less sensitive to LAI but more sensitive to Chl with sensitivity value of 0.37 and 0.38 respectively. So NDVI, MSR and RVI are selected as the input variables of cost-functions to inverse LAI via LUT method.

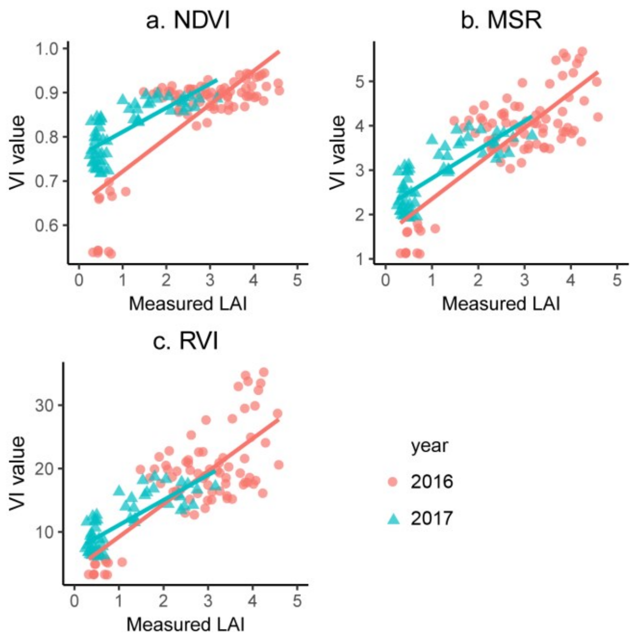

Fig. 5 Scatter graph between VIs and measured LAI

TABLE VI. CORRELATION COEFFICIENT BETWEEN VEGETATION INDICES AND MEASURED LAI

Year	NDVI	MSR	RVI
2016	0.72	0.82	0.82
2017	0.80	0.80	0.76
total	0.76	0.80	0.81

C. LAI inversion based on LUT method

In order to compare different input variables of the cost-functions, this study selected five groups: (1) three VIs (NDVI,RVI,MSR); (2) green, red, red-edge and NIR bands; (3) green and red bands; (4) red and NIR bands; (5) green, red and red-edge bands. Table.V demonstrated the correlation coefficients value between estimated LAI and measured LAI. In this study, the inversion accuracy of group (3) is the highest, with the correlation coefficients value of 0.85 and lowest value of RMSE and MRE. Estimation accuracy of group (1) ranks the second. These three VIs in group (1) are only calculated from the red and NIR band. Compared with group (3), correlation coefficients of group (2) is higher, which indicates that the LAI estimation accuracy of VIs as the input variables of cost-functions is better than that of the single bands when the bands used are the same. Red-edge band is ruled out in group (5), since the correlation coefficient between this band and LAI is poor. Contrasting group (2) and (3), or group (3) and (5), the number of bands isn't necessary for the higher estimation accuracy, but the applicability of bands for LAI inversion.

As Table.V shows, the estimation accuracy of various cost-functions is different. Accuracy of χ_{RMSE} cost-function is better than that of χ_{RRMSE} cost-funciton when VIs are the input variables, but there is no significant difference to group (3). Fig. 6 is the scatter plot of the measured LAI and estimated LAI. It can be seen from the plot that the estimated LAI was significantly higher than the measured LAI. The destructive sampling method only measured the area of leaves, neglecting the stems and spikes of wheat. However, LAI information obtained from aerial remote sensing images includes leaves, stems and spikes of wheat, therefore, the measured LAI value was lower.

TABLE V. DIFFERENT CONSTRAINTS IN COST-FUNCTIONS OF LUT METHOD FOR LAI INVERSION

		(1) VIs		**(2) G+R+E+NIR**	
Cost-function		χ_{RRMSE}	χ_{RMSE}	χ_{RRMSE}	χ_{RMSE}
r		0.76	0.78	-0.20	0.18
RMSE		1.22	1.19	2.37	2.73
MRE		1.17	1.15	2.77	3.25
(3) G+R		**(4) R+NIR**		**(5) G+R+NIR**	
χ_{RRMSE}	χ_{RMSE}	χ_{RRMSE}	χ_{RMSE}	χ_{RRMSE}	χ_{RMSE}
0.85	0.85	0.42	0.18	0.29	0.18
0.82	0.82	2.41	2.73	2.61	2.73
0.41	0.41	2.59	3.25	3.02	3.25

Note: G is green band, R is red band, E is the red-edge band, NIR is near infrared red band

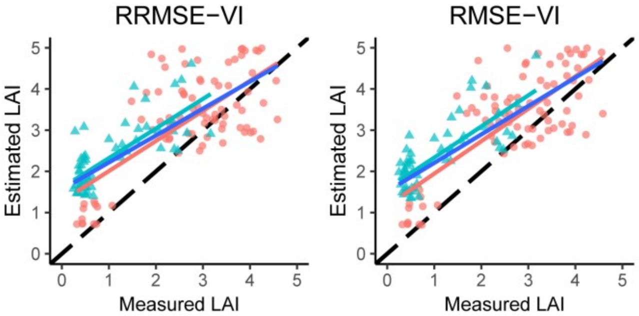

Fig.6 Comparison between measure LAI *in situ* and the estimated LAI when VIs are the input variables of cost-functions

IV. CONCLUSION

Global sensitivity analysis of PROSAIL model is of great significance to the inversion of LAI when using LUT method due to the complication of obtaining all input variables value in model. In this study, for the single band, results of the EFAST global sensitivity analysis show that green and red bands are sensitive to LAI. The group including these two bands as the input variables of cost-functions is applicable for LAI inversion, with the higher correlation coefficients and lower RMSE and MRE. For the VIs in this study, the most sensitive input variables of PROSAIL model are LAI, ALA and Chl. VIs of MSR, RVI and NDVI are considerably more sensitive to LAI than Chl and relatively insensitive to ALA. Estimated LAI from LUT method with NDVI, MSR and RVI as input variables of cost-functions is positively correlated to measured LAI, with correlation coefficient value over 0.75, indicating that it may be an alternative way to inverse LAI.

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