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Research Article

Genetic Algorithm based Inversion Modelling of PROSAIL for Retrieval of Wheat Biophysical Parameters from Bi-directional Reflectance Data

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ABSTRACT

Canopy reflectance model inversions are widely used for estimation of vegetation properties from remote sensing, but the inversion accuracy needs significant improvements. In recent years, applications of the genetic algorithms (GA) to a variety of optimization problems in remote sensing have been successfully demonstrated. The present study is focused on the GA based inversion approach of radiative transfer model 'PROSAIL', for the retrieval of LAI, leaf chlorophyll content (Cab), canopy chlorophyll content (CCC) and leaf wetness (Cw) of wheat from field-measured spectral reflectance in the whole spectral range (400-2500nm) and in broad bands corresponding to MODIS, TM and IRS LISS-3sensors. Performance of inversion was evaluated for both broadbands and the whole spectral range (400-2500 nm). The estimation accuracy was in the order of LAI>CCC>Cab> Cw. The retrieval accuracy of Cw was poor, although the estimate from whole spectra reflectance was better than that from broadband reflectance.

Key words: Genetic algorithm, PROSAIL, Leaf area index, Chlorophyll content, Bi-directional reflectance

Introduction

Remote sensing observations have been successful in providing reliable and quantitative estimates of canopy biophysical properties, such as leaf area index (LAI), chlorophyll content (Cab) and leaf wetness (Cw). Knowledge of these variables are extremely important for several applications *e.g.,* site-specific crop management in precision agriculture (Casa *et al.*, 2010), crop monitoring, yield estimations and using ecosystem productivity models from regional to global scales, for understanding growth dynamics in plant communities (Hilker *et al.*, 2012) and as bio-indicators of vegetation stress (Zarco-Tejada *et al.*, 2001). Inversion of radiative transfer models (RTMs) efficiently estimates biophysical variables from remote sensing (Jacquemoud *et al.*, 2000; Weiss *et al.*, 2000), as local calibration is not required. The empirical relationship of vegetation indices and biophysical parameters is sensitive to vegetation type and soil background. It is difficult to apply to a large area because the relationship may not be stable even if information on surface cover type is used. Among all RTMs, PROSAIL model is popular and widely applied and it describes both the spectral and directional

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variations of canopy reflectance as a function of leaf biochemistry and canopy architecture (Jacquemoud *et al.*, 2009). Model inversion, however, requires significant computational resources which are slow on large data sets. Different inversion techniques have been proposed for radiative transfer model are numerical optimization methods (Jacquemoud *et al.*, 2000; Meroni *et al.*, 2004), look-up table (LUT) approaches (Burman *et al.,* 2010; Tripathi *et al.,* 2012), artificial neural networks (Kravchenko, 2009), Principal component inversion technique (Satpathy and Dadhwal, 2005), support vector machine based regression (Durbha *et al.*, 2007) and genetic algorithm (Fang *et al*., 2003). A limitation shared by all of the physically based models is the ill-posed nature of model inversion (Atzberger, 2004); the fact that different combinations of canopy parameters may correspond to almost similar spectra (Houborg and Boegh, 2008). Applications of genetic algorithms (GA) to a variety of optimization problems in remote sensing have only been demonstrated in recent years. The fundamental concept of GA is based on the natural selection in the evolutionary process, which is accomplished by genetic recombination and mutation (Goldberg, 1989). For a traditional optimization inversion algorithm, the final solution is often affected by the initial values. Therefore, the solution obtained through an iterative process is reliable only if the space of initial conditions is sufficiently scanned (Bicheron and Leroy, 1999). The most significant advantage of the GA is that it avoids the initial guess selection problem and provides a systematic scanning of the whole population and several acceptable local solutions such that a global optimum solution could be identified. Keeping in view of the above, a field study was undertaken to evaluate the retrieval of LAI, Cab, CCC and Cw of wheat through PROSAIL model using GA technique. The GA inversion approach was implemented corresponding to broadband reflectance of Terra MODIS, Landsat TM and IRS LISS-3 sensors.

Materials and Methods

A field experiment was conducted with wheat (*Triticum aestivum* L. var. PBW-502) in the experimental farm of Indian Agricultural Research Institute, New Delhi during *rabi* 2010-2011 with all recommended agronomic practices. The crop LAI, average leaf angle (angl), leaf chlorophyll content (Cab), specific leaf weight (Cm), leaf moisture (Cw), leaf length, canopy height and dry biomass were measured following standard procedures, synchronizing with the spectral observations taken at different growth stages of the crop.

Bi-directional reflectance measurements

The bi-directional reflectance measurements at different relative azimuth and view zenith angles were taken using ASD FieldSpec-3 hand held spectroradiometer along with a portable field goniometer at 3 dates corresponding to different crop growth stages. The spectroradiometer has a default 25° field of view which was modified to make it 10° using fore-optics provided with the instrument. The wheat reflectance were measured in the spectral range of 350-2500 nm at 8 relative azimuthal angles (*i.e.*, relative to the azimuth angle of sun) (0, 45, 90, 135, 180, 225/-135, 270/-90 and 315°/-45°) and in 6 zenith angles (20, 30, 40, 50 and 60°, and at nadir). A detailed study was done to find the hotspot position among all possible combination of view zenith and azimuth angles as model inversion performed best at hotspot position.

Radiative transfer model-PROSAIL

The PROSAIL (Jacquemoud *et al*., 2009) is a combination of two models, the PROSPECT that describes leaf optical properties and the SAIL model that computes canopy reflectance. The PROSAIL requires detailed information on leaf optical properties and it also accounts for the hotspot effect.

Broadband reflectance

A program in MATLAB was written to integrate 1nm interval spectro-radiometric

Table 1. Starting, ending and central wavelength of Terra MODIS, Landsat TM and IRS

Band	Starting wavelength (nm)			Ending wavelength (nm)			Central wavelength (nm)		
	MODIS	TM	LISS3	MODIS	TM	LISS3	MODIS	TM	LISS3
B1	620	450	450	670	520	650	645	469	568
B2	841	520	550	876	600	750	858	555	660
B3	459	630	700	479	690	918	469	660	790
B4	545	760	1550	565	900	1750	555	830	1634
B5	1230	1550		1250	1750		1240	1640	
B6	1628	2080		1652	2350		1640	2130	
B7	2105			2155			2130		

reflectance measurements of the crop to broadband reflectance corresponding to optical bands of Terra MODIS, Landsat TM and IRS LISS-3 sensors using their respective band-wise relative spectral responses (RSR). The starting, ending and central wavelengths of LISS-3, TM and MODIS sensors are given in Table 1. The broadband reflectance values were further used in GA based inversion approach to retrieve corresponding wheat biophysical parameters.

Inversion approach-genetic algorithm

Genetic algorithm (GA) was used to retrieve plant biophysical parameter. This method is an iterative search algorithm based on an analogy with the process of natural selection and evolutionary genetics. The search aims to optimize a user-defined function called the fitness function by maintaining a population of ‘candidate points’, called ‘individuals’, over the entire search space. At each iteration, called a ‘generation’, a new population is created. This new ‘generation’ consists of individuals which fit better than the previous ones. Through iterations, the individuals will tend toward the optimum of the fitness function. Three important features distinguish the GA approach: a) it works in parallel on a number of search points (potential solutions) and not on a unique solution; b) it requires only an objective function measuring the fitness score of each individual and no other information nor assumptions such as derivatives and differentiability; and c) both selection and recombination steps are performed by using probability rules rather than deterministic ones; this aims to maintain the global explorative properties of the search.

Reflectance simulation using PROSAIL

Out of total 14 variables required to simulate the reflectance by PROSAIL, only 3 are free variables *e.g.*, Cw, Cab, and LAI. The range of these variables was defined by *a priori* knowledge from the field observation and those reported in literature. The variables for wheat were taken as 0.01-0.045 cm for Cw, 30-100 µg.cm^{-2} for Cab and 0.5-6.5 for LAI. Parameters like Car, skyl were given the model default values (*e.g.*, Houborg *et al.*, 2007), or values taken from the literatures. The values of other fixed parameter Cbrown was taken as 0.05, Cm as 0.0046 g cm^{-2} as per measurements, N as 1.0 and *psoil* as 0.1 for wheat crop. The *angl* values for each observation date were given as measured in the field. The view zenith angle was set at hotspot position *i.e.*, 40^{o} in the backscattering direction of principal plane (*i.e.*, relative azimuth of 0°). As the sun illumination geometry varied during the growing season, sun zenith angles of 51^{o}, 45° and 33° corresponding to 46, 48 and 106 DAS were used. A program in MATLAB was written to simulate reflectance using fixed and range of free PROSAIL parameters.

Coupling of GA with PROSAIL model

Programs were written in MATLAB for separate fitness functions in whole spectra reflectance and broadband reflectance (MODIS, TM and LISS-3). At each iteration, the values of free parameters were taken randomly from the defined range of those free parameters to simulate reflectance and then evaluate fitness function. The parameters, mean squared error (MSE) or *nash-sutcliffe efficiency* (NSE) were used for fitness function. It was found that MSE performed better than NSE, and hence MSE was used for subsequent analysis. The MSE and NSE was calculated as:

$$\text{MSE}= \sum_{i=1}^{n} \frac{(Robs-Rsim)2}{n} \qquad \ldots(1)$$

where, *Robs* = observed reflectance, *Rsim*= simulated reflectance, n = number of observations

and $$\text{NSE}=1- \frac{\sum_{i=1}^{n}(Oi-Pi)\hat{}2}{\sum_{i=1}^{n}(Oi-\bar{O})\hat{}2} \qquad \ldots(2)$$

where, *Oi* and *Pi* are observed and simulated reflectance at specific wavelength band i, *O* = mean of observed reflectance, and n = number of wavelength bands.

Separate fitness function files were prepared for three observation dates.

To carry out this technique, GA optimization toolbox in MATLAB was used for retrieval of wheat biophysical parameters. Among various GA parameters, 'creation function' was set as 'feasible population', 'mutation function' as 'adaptive feasible', 'crossover function' as 'scattered' and 'selection type' as 'stochastic uniform'. During trials with GA parameters, it was observed that different GA parameters had different degree of influence on final result. Two of them such as 'population size' and 'crossover fraction' were shown in Fig. 1 as an example to present how it affects on fitness values.

With increase in population size, fitness value reduces insignificantly, while crossover fraction did not show any specific trend, and hence default value of 0.8 was used.

Evaluation of GA inversion approach

The parameters retrieved using GA inversion approach was compared with the field-measured values. Determination of coefficient (R^2), root mean square error (RMSE), normalized RMSE (nRMSE) and ratio of deviation to prediction (RDP) between measured and model retrieved values were computed and used as measures of evaluation. Model prediction is good when RDP value is greater than 1 and poor when it is less than 1.

$$\text{RMSE}= \sqrt{\sum_{i=1}^{n} \frac{(Pobs-Psim)2}{n}} \qquad \ldots(3)$$

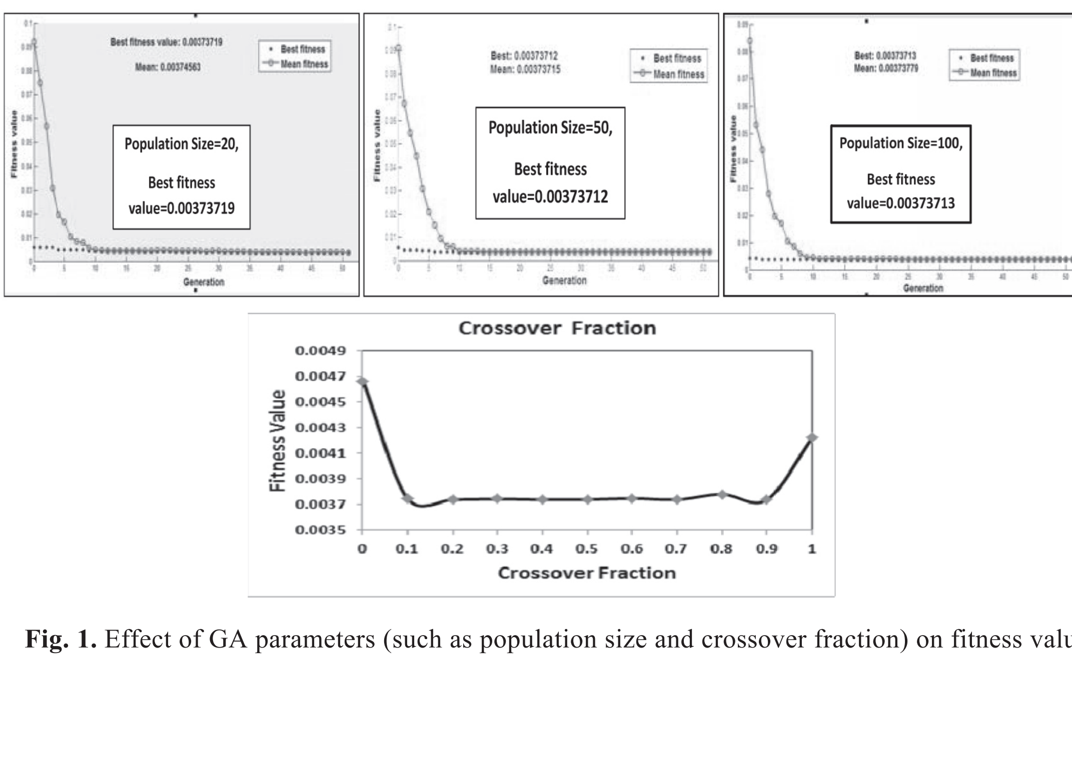

Fig. 1. Effect of GA parameters (such as population size and crossover fraction) on fitness value

where, P*obs* and P*sim*= Observed and estimated parameter values, n = number of observations; nRMSE=RMSE/mean measured value, and RDP= standard deviation/RMSE

Results and Discussion

Crop biophysical parameters

The bi-directional measurements at 46, 68 and 106 days after sowing (DAS) were corresponded to tillering, vegetative growth (jointing and elongation) and grain filling (milk) stages (Table 2). This set of observed parameters thus could be a representative set to use for PROSAIL model validation accounting for a range of wheat growth conditions.

Retrieval of biophysical variables using GA inversion

The scatter plot of observed versus estimated values are shown in Figs. 2, 3, 4 and 5. The performance of retrieval of biophysical parameters is summarized in Table 3. Observed LAI values varied between 0.5 to 3.2 and the estimated LAI varied between 0.66 to 2.61 for MODIS, 0.63 to 2.6 for TM, 0.75 to 2.5 for LISS-3 and 0.63 to 2.2 for the whole spectra. There was over and underestimation of LAI at lower and higher range, respectively. Retrieval of LAI was satisfactory for both broadband and whole spectra reflectance with maximum R^2 of 0.926 (p=0.0021) with LISS-3. Observed values of Cab varied between 28 and 64. The estimated values were 57-69 for MODIS, 45-69 for TM, 49-68 for LISS-3 and 30-63 for whole spectra with the maximum R^2 of 0.91 (0.003) for whole spectra. The observed values for CCC varied between 0.96-2.05 and the estimated values varied between 0.2-1.2 for MODIS, 0.19-1.19 for TM, 0.22-1.33 for LISS-3 and 0.2-1.2 for whole spectra. The observed values of Cw varied between 0.014-0.018 and estimated values varied between 0.021-0.036 for MODIS and 0.025-0.034 for TM, 0.024-0.034 for LISS-3 and 0.014-0.034 for whole spectra. Whole spectra resulted in better estimates of Cw (R^2=0.58 at p=0.078). The RDP values indicate better accuracy for LAI than the other parameters.The GA approach predicted LAI, Cab and CCC with good level of accuracy as shown

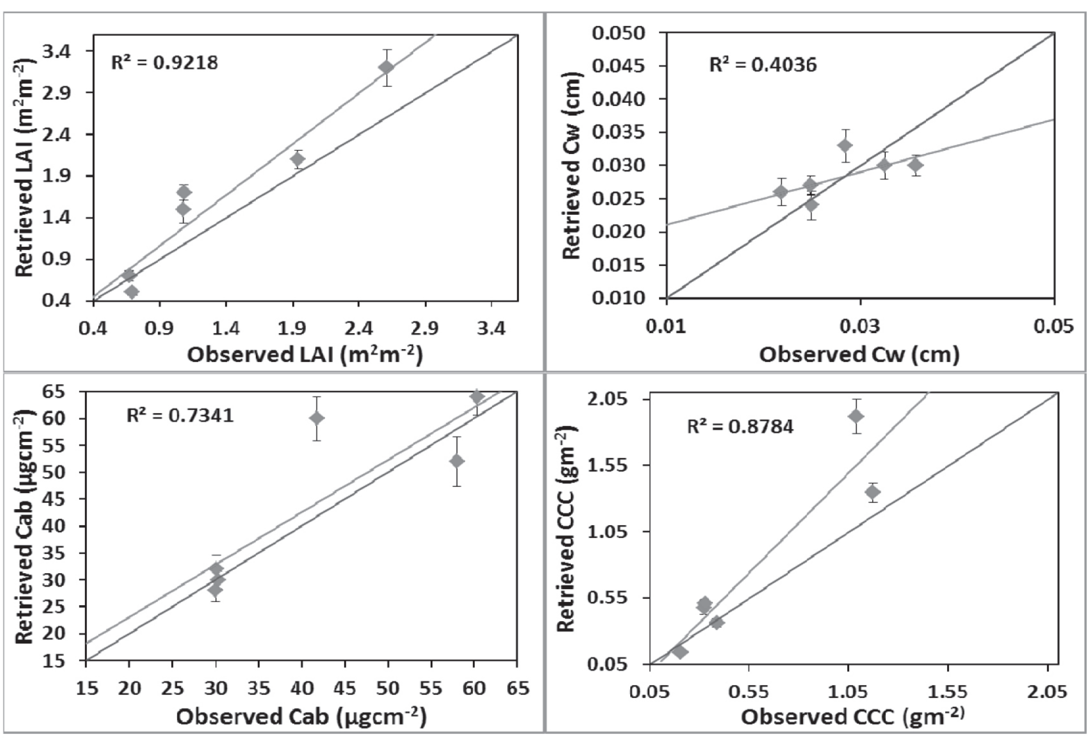

Fig. 2. Scatter plot of observed vs. retrieved values by GA inversions for MODIS in wheat

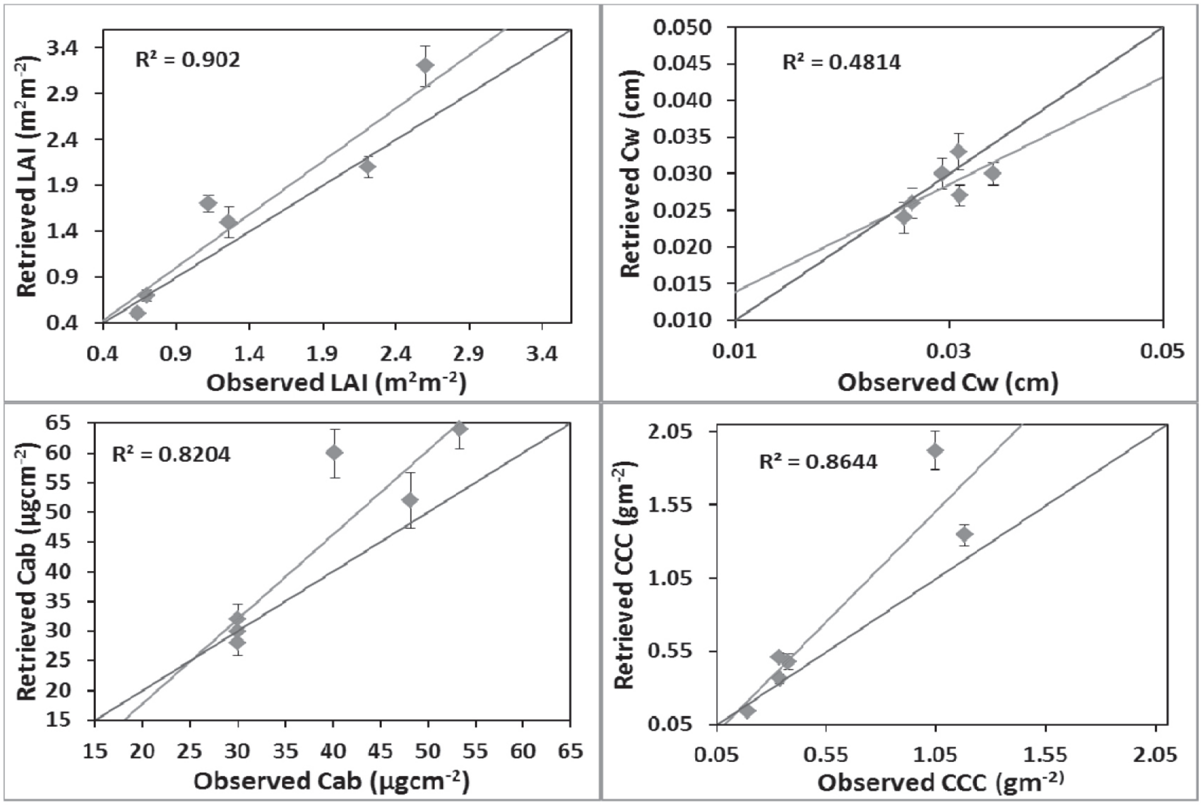

Fig. 3. Scatter plot of observed vs. retrieved values by GA inversions for TM in wheat

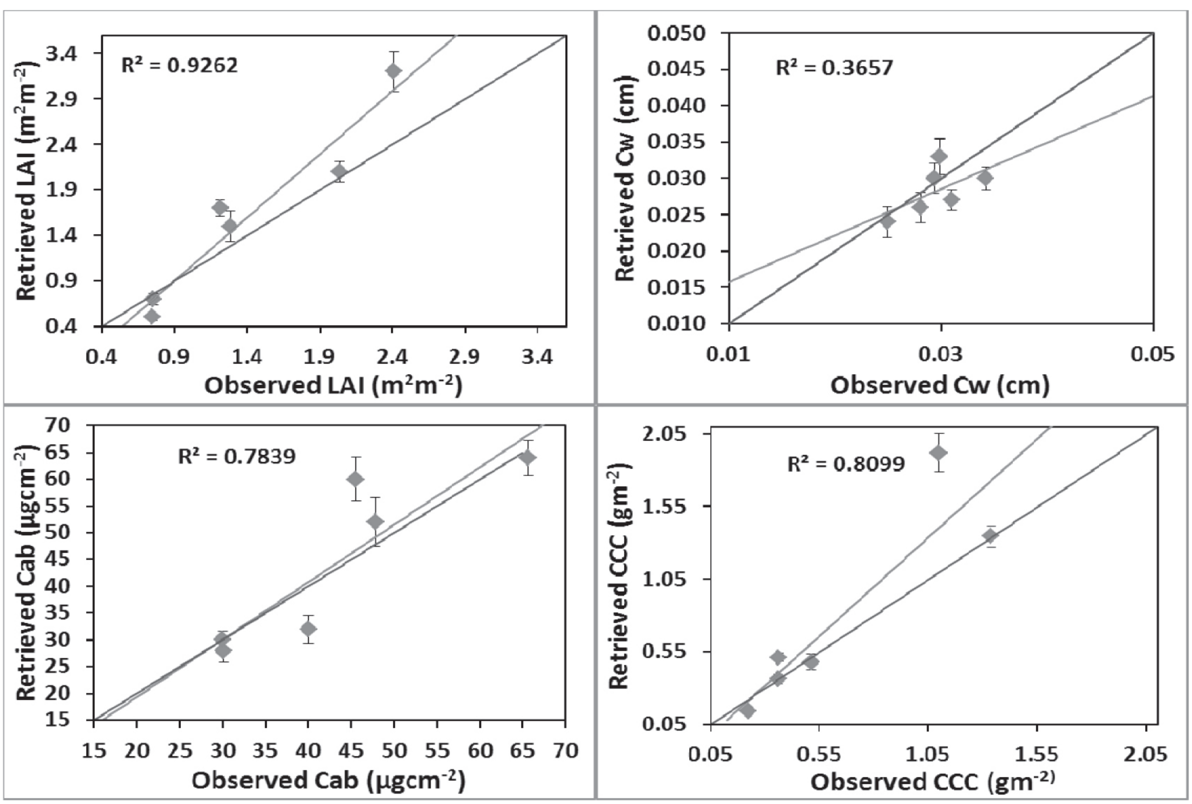

Fig. 4. Scatter plot of observed vs. retrieved values by GA inversions for LISS-3 in wheat

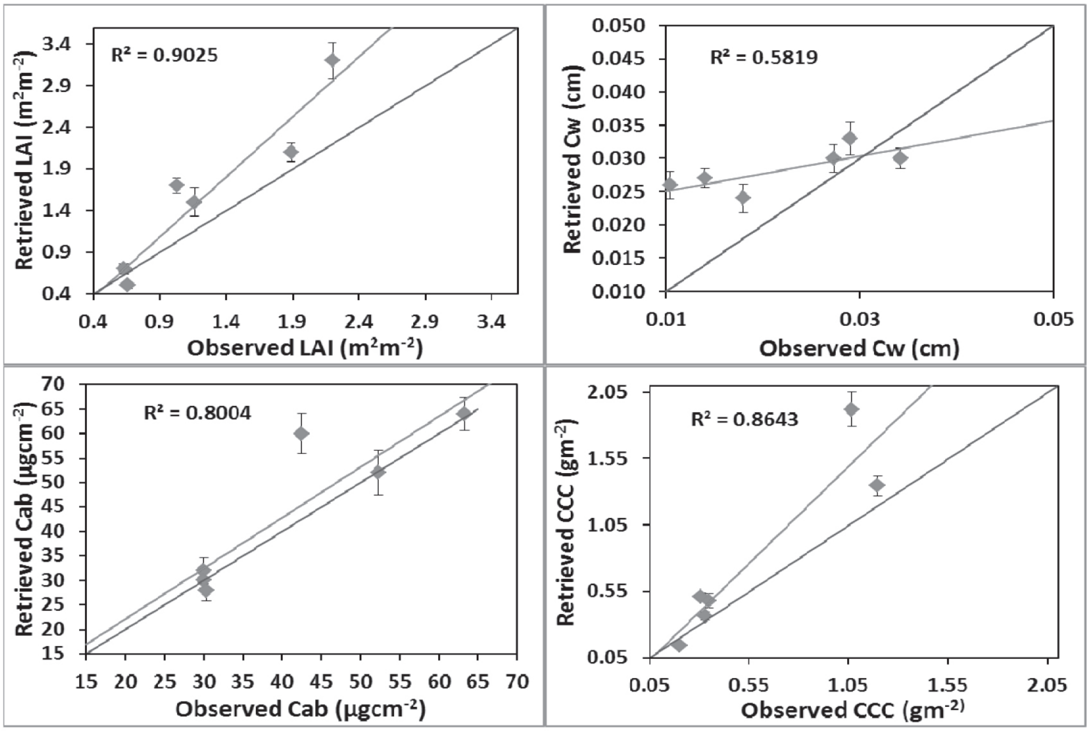

Fig. 5. Scatter plot of observed vs. retrieved values by GA inversions for whole spectra in wheat

by the estimated values lying close to 1:1 line (Figs. 2, 3, 4 and 5).

In case of Cab, low values were over estimated and high values were underestimated. An overall under estimation was found almost for all values of LAI. No trend was found in case of Cw retrieval.

The order of estimation accuracy was LAI > CCC >Cab >Cw. The level of retrieval accuracy varied among the sensors and whole spectra retrieval without showing any significant differences. The higher accuracy of LAI estimation may be due to fact that structural variables (*e.g.*, LAI) determine the total canopy reflectance of crops much more significantly than the biochemical variables (Vohland and Jarmer, 2008). The high sensitivity of Red and NIR bands and moderate sensitivity of green bands to changes in LAI (Jacquemoud *et al.*, 2009) might have resulted in a better simulation of the reflectance spectra by PROSAIL. The relationships between measured and estimated leaf chlorophyll Cab were poor compared to LAI as indicated by lower R^2 values and higher nRMSE. This corroborates with previous studies

Table 2. Wheat biophysical parameters at different days after sowing.

Parameters	Days after sowing		
	46	68	106
Chlorophyll content ($\mu g\ cm^{-2}$)	52	58	65
Leaf area index (m^2m^{-2})	0.6	2.1	3.2
Average leaf angle (degrees)	70	57	45
Leaf length /Plant height	0.78	0.4	0.32
Specific leaf weight ($g\ cm^{-2}$)	0.0046	0.0047	0.0047
Leaf moisture (cm)	0.024	0.030	0.030

Table 3. Comparison of retrieval of wheat biophysical parameters for MODIS, TM, LISS-3 and whole spectra reflectance

Estimated parameters		R^2	p value	RMSE	nRMSE	RDP
LAI (m^2m^{-2})	MODIS	0.922	0.0024	0.401	0.248	2.455
	TM	0.902	0.0037	0.362	0.224	2.723
	LISS-3	0.926	0.0021	0.403	0.249	2.444
	Whole spectra	0.903	0.004	0.523	0.323	1.883
Cab (µg cm^{-2})	MODIS	0.734	0.0293	8.069	0.182	2.010
	TM	0.820	0.0129	9.38	0.212	1.729
	LISS-3	0.784	0.0190	7.04	0.159	2.303
	Whole spectra	0.80040	0.016	7.254	0.164	2.236
CCC (g m^{-2})	MODIS	0.878	0.0058	0.361	0.455	1.906
	TM	0.864	0.0072	0.373	0.471	1.842
	LISS-3	0.810	0.0145	0.343	0.432	2.006
	Whole spectra	0.864	0.007	0.368	0.464	1.869
Cw (g cm^{-2})	MODIS	0.404	0.1753	0.004	0.130	0.884
	TM	0.481	0.1263	0.003	0.092	1.246
	LISS-3	0.366	0.2035	0.003	0.101	1.137
	Whole spectra	0.582	0.078	0.009	0.319	0.362

(Darvishzadeh *et al*., 2008). It may be explained as poor signal propagation from leaf to canopy resulting in weak estimation of leaf biochemical parameters by canopy reflectance (Asner, 1998). Moreover, it is only the visible bands sensitive to leaf chlorophyll variation, which has low dynamic range due to dominance effect of absorption. So, there may be greater chance of error in simulated reflectance of PROSAIL in these bands, leading to poorer estimate of leaf chlorophyll. In the case of leaf water content (Cw), retrieval was poor for all broadband reflectance as indicated by non-significant R^2 values. Although Cw retrievals using whole spectra range reflectance was better.

Conclusions

This work evaluated the inversion approach of GA for concurrent retrieval of biophysical parameters of LAI, Cab, CCC and Cw and showed that it could capture the variability in measured wheat biophysical parameters with the order of accuracy as LAI > CCC > Cab > Cw. The study demonstrates that the GA optimization method may provide an alternative to invert the radiative transfer models in remote sensing.

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