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Inversion of radiative transfer model for retrieval of wheat biophysical parameters from broadband reflectance measurements

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A B S T R A C T

This study describes the retrieval of wheat biophysical variables of leaf chlorophyll (C_{ab}), leaf area index (LAI), canopy chlorophyll (CCC), and leaf wetness (C_w) from broadband reflectance data corresponding to IRS LISS-3 (Linear Imaging Self Scanner) sensor by inversion of PROSAIL5B canopy radiative transfer model. Reflectance data of wheat crop, grown under different treatments, were measured by hand-held spectroradiometer and later integrated to LISS-3 reflectance using its band-wise relative spectral response function. Three inversion techniques were used and their performance was compared using different statistical parameters and target diagram. The inversion techniques tried were: a look up table with best solution (LUT-I), a look up table with mean of best 10% solutions (LUT-II) and an artificial neural network (ANN). All the techniques could estimate the biophysical variables by capturing variability in their observed values, though accuracy of estimation varied among the three techniques. Target diagram clearly depicted the superiority of LUT-II over the other two approaches indicating that a mean of best 10% solutions is a better strategy while ANN was worst performer showing highest bias for all the parameters. In all the three inversion techniques, the general order of retrieval accuracy was LAI > C_{ab} > CCC > C_w. The range of C_w was very narrow and none of the techniques could estimate variations in it. In most of the cases, the parameters were underestimated by model inversion. The best identified LUT-II technique was then applied to retrieve wheat LAI from IRS LISS-3 satellite image of 5-Feb-2012 in Sheopur district. The comparison with ground observations showed that the RMSE of LAI retrieval was about 0.56, similar to that observed in ground experimentation. The findings of this study may help in refining the protocol for generating operational crop biophysical products from IRS LISS-3 or similar sensors.

1. Introduction

The distribution of vegetation biochemical and biophysical variables in both spatial and temporal extent are important inputs into models quantifying the exchange of energy and matter between the land surface and the atmosphere,

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developing better yield prediction models and detecting abiotic stresses at regional scales. Among various vegetation parameters, leaf chlorophyll content (C_{ab}) and leaf area index (LAI) are of foremost significance [1]. Leaf area index can be used to infer about several ecological processes (e.g., photosynthesis, transpiration and evapotranspiration), estimate net primary production (NPP) of terrestrial ecosystems and is also used in the biosphere–atmosphere interaction models in some General Circulation Models [2]. At the same time monitoring spatial patterns in the biochemical composition of plant foliage is required for understanding the growth dynamics of plant communities [3] and serve as bio-indicators of vegetation stress [4]. The stability, repeated measurement capability, cost effectiveness and global coverage of remote sensing techniques has led to its widespread use to obtain these variables in studies of land surface and atmospheric processes [5,6].

Remote Sensing measurement of plant biophysical parameters can broadly be classified into empirical and analytical/-physical approaches [7,3]. Empirical techniques mostly depends on linear and non-linear combinations of discrete spectral reflectance bands i.e. vegetation indices (VIs) which are used to maximize sensitivity to canopy characteristics while minimizing sensitivity to other, unrelated phenomena such as background effects and viewing geometry [3]. Both approaches have their advantages and disadvantages. The simplicity and computational efficiency of empirical approach makes it highly amenable for large-scale remote sensing applications. However, lack of generality of scale of application remains a fundamental problem with the VIs approach for estimating vegetation parameters. As canopy reflectance results from complex interaction of several internal and external factors [8] which varies significantly in time and space and from one crop type to another, relationship between a single canopy variable and a spectral signature can hardly be expected to be unique [5]. Further, the anisotropic properties of the surface features makes it more complex and to vary with different view angles. Hence, spectral reflectance relationships are site, time and crop specific, making the use of a single relationship for an entire region unfeasible [9].

On the other hand, the analytical/physically-based models describe the transfer and interaction of radiation inside the canopy based on physical laws and thus providing explicit relation between the biophysical variables and the canopy reflectance [5]. Therefore, retrieving canopy characteristics from the inversion of these models is theoretically preferable to fully exploit the information contained in the reflectance signal recorded by remote sensing sensors [10]. Knowledge of the relationship between canopy biophysical characteristics to surface reflectance anisotropy [11,12] provides a strong scientific basis for the application of these models [13]. However, this approach is limited by several aspects not only from the complexity of canopy radiation interaction processes but also from the inversion techniques [14,15]. Selection of appropriate model is often a trade-off between model complexity, invertibility and computational efficiency [14]. The advancement in modeling through detailed radiation interaction descriptions offer great potential for improvement but requires an extensive description of canopy architecture and high computational efficiency [10]. On the other hand from the application side, because of the lack of prior information on the statistical distribution of most land surface attributes, simple low-dimensional radiative transfer models are often preferred for operational purposes [10].

Inversion of physics-based radiative transfer models has grown rapidly in the field of remote sensing of both aquatic and terrestrial environments [16,17]. Different inversion techniques have been proposed for these models, including numerical optimization methods [18–20], look-up table (LUT) approaches [21–23,1,24], artificial neural networks (ANN) [25,14,26,27], genetic algorithm (GA) [28], Principal Component Inversion (PCA) technique [29] and, very recently, support vector machines (SVM) regression [30–32]. The iterative optimization approach can directly retrieve biophysical parameters from observed reflectance without any sort of prior use of calibration or training data. But this method lags behind for its expensive computational requirement [19] making the retrieval of variables unfeasible for large areas. The LUT and ANN methods are computationally efficient than the traditional optimization approach and can be applied on a per pixel basis of satellite images. Moreover, they can be applied to the most sophisticated models without any simplifications. Though look up table technique may provide an efficient alternative, the definition of the cost function to be minimized still remains an open question when the uncertainties and their structure are not very well known [10]. These limitations are sorted out by neural networks which have been increasingly used for reflectance model inversion [33,26]. They are very efficient computationally since the inversion process is not iterative in the application mode. All of the physically based models share the common limitation of the ill-posed nature of model inversion [34,22]; which is observed with different combinations of canopy parameters corresponding to almost similar spectra [5]. Lookup table and neural network approaches require a training database consisting of canopy reflectance spectra together with the corresponding biophysical variables, and their performances rely on the training database and the training process itself.

There is still dearth of ample information on rigorous comparison of the various inversion methods in terms of accuracy and stability, computational time and number of variables obtainable [35,36]. Keeping in mind the problems of these inversion strategies, a field study followed by a regional scale study were undertaken to compare of PROSAIL5B model inversion by look up table (LUT) and neural network approaches to simultaneously derive wheat biophysical parameters of leaf chlorophyll content (C_{ab}), leaf moisture content (C_w), leaf area index (LAI) and canopy chlorophyll content (CCC). Inversion approaches were implemented corresponding to broadband reflectances of IRS LISS-3 (Indian Remote Sensing Satellite Linear Imaging Self Scanning-3) sensor. Two variants of LUT approach were tried as described later and performance of all three inversion approaches was evaluated using ground measured wheat canopy parameters at different growth stages. The best method was applied for the regional scale study. The performance of inversions was evaluated using statistical measures and target diagram.

2. Material and methods

2.1. Study sites and biophysical parameter measurements

A field experiment was conducted in the experimental farm of Indian Agricultural Research Institute, New Delhi. The cultivar PBW-502 of spring wheat (*Triticum aestivum* L.) was raised during the *rabi* (Nov–Mar) season of 2010–2011 with three nitrogen treatments viz. 0 (N_0), 60 (N_{60}) and 120 (N_{120}) kg ha^{-1}, each with two replications. The treatments were applied to achieve a wide range of crop growth and hence crop biophysical parameters on a given date for use in the validation of PROSAIL-5B model.

Various plant parameter inputs for PROSAIL model were measured synchronizing with the spectral observations taken at different growth stages of wheat crop. Leaf area index (LAI) was measured by taking five observations in each plot using Plant Canopy Analyser (LI-2000) [37]. Leaf chlorophyll (Cab) was measured by extracting with DiMethyl SulfOxide (DMSO) and keeping it in an oven at 65 °C for about 3 h [38] followed by reading the absorbance at 645 and 663 nm wavelengths using Spectrophotometer. Plant samples were cut just above the soil surface followed by separation of leaves and measurement of the area of fresh leaves by passing them through leaf area meter (LI-3100). These leaves were dried at 70 °C to achieve constant weight and then their dry weight was measured. Equivalent leaf moisture thickness (Cw), an index of leaf water content which represents volume of leaf water per unit leaf area, was calculated as the ratio of difference in the fresh and dry leaf weights to the leaf area.

This study was further extended to the regional scale for the wheat growing areas of Sheopur district of Madhya Pradesh by using IRS-P6 LISS-3 satellite image of 5th February, 2012 (path:96, row:53). Extensive ground truth of the area was undertaken synchronous to satellite pass. The LAI measurements were recorded in different wheat fields using canopy analyser (LI-2000) along with their locations using a high-sensitivity GPS receiver (Garmin 76CSx). Multiple LAI were recorded in each of the selected fields to account for with-in field variability.

2.2. Field bi-directional reflectance measurements

The bi-directional reflectance measurements at different relative azimuth and view zenith angles were taken using ASDI (Analytical Spectral Devices Incorporation) FieldSpec-3 hand held spectroradiometer installed on a portable field goniometer at different growth stages of wheat. The default 25° Field of View (FOV) of the spectroradiometer was reduced to 10° using fore-optics provided with the instrument. The reflectance were measured in the spectral range of 350–2500 nm at eight relative azimuthal angle (relative to the azimuth angle of sun) i.e. 0°, 45°, 90°, 135°, 180°, 225°/−135°, 270°/−90° and 315°/−45° and at six zenith angles (20°, 30°, 40°, 50° and 60° plus nadir). In principal plane (which is aligned to sun azimuth), the 0° relative azimuth referred to the backward scattering direction of light while 180° relative azimuth referred to the forward scattering direction of light. The spectroradiometric reflectance measurements at 1 nm interval were integrated to broadband reflectance corresponding to the four optical bands of IRS-P6 LISS-3 sensor (B1: 450–650, B2: 550–750, B3: 700–918 and B4: 1500–1750 nm) by using their respective band-wise relative spectral response (RSR) curves. These four broadband reflectances were used as input to the inversion approaches to retrieve corresponding wheat biophysical parameters.

2.3. The radiative transfer model-PROSAIL

This study employed one of the widely used canopy radiative transfer model PROSAIL [39] which is a combination of two models, i.e., the PROSPECT model [40] that describes leaf optical properties and the SAIL model [41] that computes canopy reflectance. The PROSAIL model considers detailed information on leaf optical properties and also accounts for hotspot effect. The PROSAIL-5B version of model written in IDL™ language [42] was used which incorporates PROSPECT-5 and 4SAIL models. The input parameters of PROSAIL-5B and their units are given in Table 1 [43].

2.4. Validation of PROSAIL

In order to validate the model for a given treatment on a particular day, required input parameters of leaf, canopy, soil, view and solar zenith and relative azimuth angles were provided. The model simulated canopy bi-directional reflectance between 400 and 2500 nm at 1 nm interval. The model simulated values were validated by comparing them with observed values at specific wavelengths (568, 660, 790 and 1634 nm) corresponding to the central wavelength of IRS LISS-3 sensor bands. The validation was done in the principal plane at different view zenith angles (−60°, −50°, −40°, −30°, −20°, 0°, 20°, 30°, 40°, 50°, 60°). The negative view zenith corresponded to backward scattering direction (i.e. sun behind sensor) and the positive corresponded to forward scattering direction (i.e. sensor opposite to sun). The performance of the model was evaluated by calculating Root Mean Square Error (RMSE) using the following formula:

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(R_{obs} - R_{sim})^2}{n}} \quad (1)$$

where R_{obs} = observed reflectance, R_{sim} = simulated reflectance, n = number of observations.

In order to compare RMSE across wavelength regions at various growth stages of crop, it was normalized by the average of observed reflectance values and thus normalized RMSE (nRMSE) was calculated as given below:

$$\mathrm{nRMSE} = \frac{\mathrm{RMSE}}{\mu} \quad (2)$$

where μ = average of observed reflectance values over a wave band.

2.5. Inversion approaches

In this study, mainly two inversion approaches of look-up-table (LUT) and artificial neural network (ANN) were used which are popular among the researchers for biophysical parameter retrieval.

Table 1 – Input parameters of PROSAIL-5B model used to generate LUT for wheat at three different days after sowing (DAS).

Parameter	Abbreviation	Unit	Range of values	Fixed values
Leaf chlorophyll content	Cab	$\mu g\ cm^{-2}$	20–80	
Carotenoid content	Car	$\mu g\ cm^{-2}$	–	1.0
Brown pigment content	Cbrown	Arbitrary units	–	0.05
Equivalent water thickness	Cw	cm	0.01–0.04	
Dry matter content	Cm	$g\ cm^{-2}$	–	0.0046
Leaf structure coefficient	N	No dimension	–	1.0
Leaf area index	LAI	$m^2\ m^{-2}$	0.1–6.0	
Average leaf angle	angl	Degree	70, 57, 45	
Soil coefficient	psoil	No dimension	–	0.1
Fraction of diffuse incoming solar radiation	skyl	No dimension	–	0.1
Hot-spot size parameter	hspot	$m\ m^{-1}$	0.78, 0.40, 0.32	
Hot-spot flag	Ihot	No dimension	–	1 (use hot spot)
Solar zenith angle	tts	Degree	51, 45, 33	
Sensor/view zenith angle	tto	Degree	–	0
Relative azimuth	psi	Degree	–	0

2.5.1. *The look-up table (LUT) inversion approach*

The simplest method of solving of a radiative transfer model is by the use of a LUT. A LUT potentially overcomes the limitations of the iterative optimization techniques associated with longer computation time and the risk of converging to local minima instead of global minima [35,22]. LUT shows less unexpected behavior when the spectral characteristics of the targets are not well represented by the modeled spectra [26]. A LUT was built in advance of the actual inversion through forward running of model PROSAIL-5B from *a priori* knowledge of the variation in crop biophysical parameters. For the inversion, only search operations are needed to identify the parameter combinations that yield the best fit between measured and LUT spectra. However, to achieve high accuracy for the estimated parameters, the dimension of the LUT must be sufficiently large [22,44,21]. The ranges of free variables were defined by *a priori* knowledge from the field observations recorded during the experiment and as reported in literature. A program in IDL™ language was written to generate the LUT corresponding to fixed and range of free PROSAIL input parameters (Table 1). For generation of LUT, only three free variables of chlorophyll content (C_{ab}), leaf area index (LAI) and equivalent leaf moisture thickness (C_w) were varied. Chlorophyll was varied from 20 to 80 $\mu g\ cm^{-2}$ at an interval of 1 $\mu g\ cm^{-2}$, LAI from 0.1 to 6.0 at an interval of 0.2 and C_w from 0.01 to 0.04 cm at an interval of 0.001 cm. Their combination resulted in a total of 54,000 cases. For each of these 54,000 cases, PROSAIL-5B simulated spectra was generated and integrated to four band reflectance corresponding to IRS LISS-3. The observed canopy reflectance spectra by spectroradiometer were also integrated into corresponding four IRS LISS-3 broad band reflectance. Thus, the LUT contained 54,000 parameter combinations and corresponding four band reflectance.

For getting the solution to the inverse problem for measured canopy reflectance, a cost/merit function was minimized for each simulated broadband reflectance of the LUT. In this study, relative mean square error (rMSE) was used as a cost function which was calculated as:

$$\mathrm{rMSE} = \sum_{i=1}^{n} \frac{(R_{obs} - R_{lut})^2}{R_{obs}} \tag{3}$$

where R_{obs} = observed reflectance at specific wavelength band i, R_{lut} = simulated reflectance in the LUT at that wavelength band, n = number of wavelength bands.

Here two types of methods (i.e. variants of LUT) were selected for getting the solution of the inversion problem. First one was what is generally practiced; here the solution is regarded as the set of input parameters corresponding to the observed reflectance in the LUT that provides the minimum rMSE and it is referred here as LUT-I inversion approach. But this solution is not always unique because different set of input parameters can many times yields similar reflectance which is called ill-posed problem [25,34]. To solve this difficulty and increase the consistency of the retrieved biophysical variables, final solution was chosen as the mean value of parameters corresponding to the best 100, 500, 1000 and 10% (i.e. 5400) solutions (i.e. having smallest sorted rMSE) and here it is referred as LUT-II inversion approach.

2.5.2. *Artificial neural network (ANN) inversion approach*

In this study a feed-forward back propagation neural network with three layers (input, hidden and output layer) was used. LISS-3 band reflectances were used as input layer and output layer corresponded to crop biophysical parameters of C_{ab}, C_w and LAI. The LUT of simulated values generated earlier with 54,000 cases was used for ANN training and validation. About 70% of the LUT entries were used for training i.e. adjusting of weights and rest 30% were used for validation. After completion of the training process, the sought biophysical parameters were calculated with the validation datasets. The validation was characterized on the basis of correlation coefficient (r) and MSE (Mean Square Error value) to evaluate the performance of training. Neural Network toolbox available in MATLAB™ (version 7.10) software was used to implement this inversion approach.

2.6. *Comparison of inversion techniques*

The biophysical parameters retrieved simultaneously were C_{ab}, C_w, LAI and CCC. The CCC was calculated as a product of C_{ab} and LAI. These retrieved parameters were compared with the measured values to check the performance of the inversion methods. Statistics of correlation coefficient

(Pearson's r), Root Mean Square Error (RMSE) and normalized RMSE (nRMSE) between measured and inverted values were employed for comparison. Besides, Target diagram [45] was also used to evaluate the performance of the three inversion techniques. Target diagram gives information about pattern statistics (that is linear correlation coefficient and variance comparisons) and the bias of the reference and the simulated field.

2.7. Analysis of satellite data

The IRS-P6 LISS-3 image was pre-processed for geometric corrections using ground control points collected from Survey of India maps. The image digital numbers were converted to radiance values using band-wise gain and offset values provided in the image header and then converted to reflectance by employing FLAASH (Fast Line-of-sight Atmospheric Analysis of Spectral Hypercubes) atmospheric correction model. Using ground truth, the study area was classified by maximum likelihood classifier and pixels other than wheat crop were masked out. The best performing inversion technique was applied to each wheat pixel using its reflectance in four bands. The retrieved LAI of wheat pixels were compared with the ground observed values.

3. Results and discussion

3.1. Validation of PROSAIL model

The performance of the model was judged in the principal plane across all the view zenith angles because here surface reflectance anisotropy is more sensitive to canopy biophysical characteristics [11]. Fig. 1 shows the comparison of model simulated reflectance with observed values at four wavelengths (568, 660, 790, and 1634 nm) in the principal plane (for $-60°$ to $+60°$ view zenith) for N_0 and N_{120} on 68 days after sowing (DAS). In terms of reflectance magnitude, the performance of the model showed reasonably good match in both the treatments. In both N_0 and N_{120} treatments, the model underestimated reflectance in backward scattering especially close to hotspot. The magnitude of underestimation was more in the backward scattering direction particularly at 568 nm. In case of N_0, close match was observed at 790 and 1634 nm in comparison to 568 and 660 nm. Andrieu et al. [46] also observed that the relative difference between measured and simulated reflectances were lower in NIR than in the VIS region for sugar beet. It may be because in VIS region, absorption of radiation dominates while in NIR mostly scattering dominates. So, even small inconsistencies at shorter wavelengths become relatively large while opposite happens at longer wavelengths [13].

Model simulations were much better in N_{120} than in N_0 at all four wavelengths of 568, 660, 790 and 1634 nm as indicated by lower RMSE values. The model performance significantly improved at 568 and 660 nm in N_{120} over N_0. This is mainly due to the fact that in sparse canopies due to higher exposure of soil, the scattering properties of vegetation and soil combine to form a unique reflectance distribution which may not be captured in PROSAIL. Moreover, in SAIL model soil is assumed to be Lambertian reflector [47] though soil shows a strong anisotropic behavior [48]. SAIL showed high soil reflectance sensitivity in RED and NIR bands when corn canopy was low [2]. Verhoef and Bach [49] while using GeoSAIL, a variant of SAIL, also recommended that for a more realistic modeling of the BRDF of sparse canopies, it will be necessary to incorporate the non-Lambertian reflection characteristics of bare soils into the GeoSAIL model. Observed reflectance showed a bowl shape with view zenith angle at all the wavelengths but this shape was very prominent at 790 nm indicating that off-nadir angles causes increase in reflectance. A close match was obtained between observed and model simulated reflectance at 790 nm. As this wavelength region is sensitive to LAI and LAD [39] it indicates that model's assumptions of canopy as horizontally homogeneous, where leaves absorb, reflect, and transmit radiation [41] hold good.

3.2. Inversion of PROSAIL model

The PROSAIL model was inverted using three inversion techniques, viz. LUT-I, LUT-II and ANN. Three plant parameters of C_{ab}, LAI and C_w were retrieved from the inversion. Then the fourth parameter of CCC was calculated as a product of C_{ab} and LAI. In case of LUT-II, instead of one unique solution multiple solutions were used in parameter retrieval. Corresponding to each observed spectra, the LUT was sorted on rMSE in ascending order i.e. lowest to highest. Then best (smallest rMSE) 100, 500, 1000 and 10% LUT entries were chosen and mean of parameter corresponding to this set was the final solution. The "Best Fit" solution shown in Table 2 refers to LUT-I approach whereas "Best 100" to "Best 10%" are various solution sets of LUT-II approach. With the increase in number of best solutions, the estimation accuracy improved as shown by successively decreasing RMSE and nRMSE values for all the parameters. The error was lowest for "Best 10%" solutions; therefore we have referred it as LUT-II in further analysis.

The comparisons of observed versus estimated values of C_{ab}, LAI, C_w and CCC corresponding to LISS-3 measured reflectances by LUT-I, LUT-II and ANN approaches are graphically shown in Fig. 2 as scatter plot around 1:1 line. The results showed different levels of accuracy for different biophysical parameters. In case of C_{ab}, significant correlation coefficient of 0.87, 0.78 and 0.71 was obtained for ANN, LUT-I and LUT-II, respectively (Table 2), indicating that all the approaches could capture the variations in C_{ab}. But the RMSE values for ANN, LUT-I and LUT-II were 23.27, 18.3 and 9.06, respectively, which showed a reverse trend to correlation. Both ANN and LUT-I showed underestimation in C_{ab} retrieval, whereas LUT-II showed both under and overestimation, equally spread above and below 1:1 line. The inversion techniques were able to capture the variations of LAI in a much better way which is indicated by the high values of correlation coefficient. Similar to the C_{ab}, the correlation coefficient for LAI and CCC is in the order of ANN > LUT-I > LUT-II, whereas the RMSE showed reverse trend i.e. ANN < LUT-I < LUT-II. Correlation coefficient and RMSE (Root Mean Square Error) are two separate pattern statistics which explains specific characteristics of the data. Now it is a situation where we should decide which of the indicators should be given more emphasis while deciding

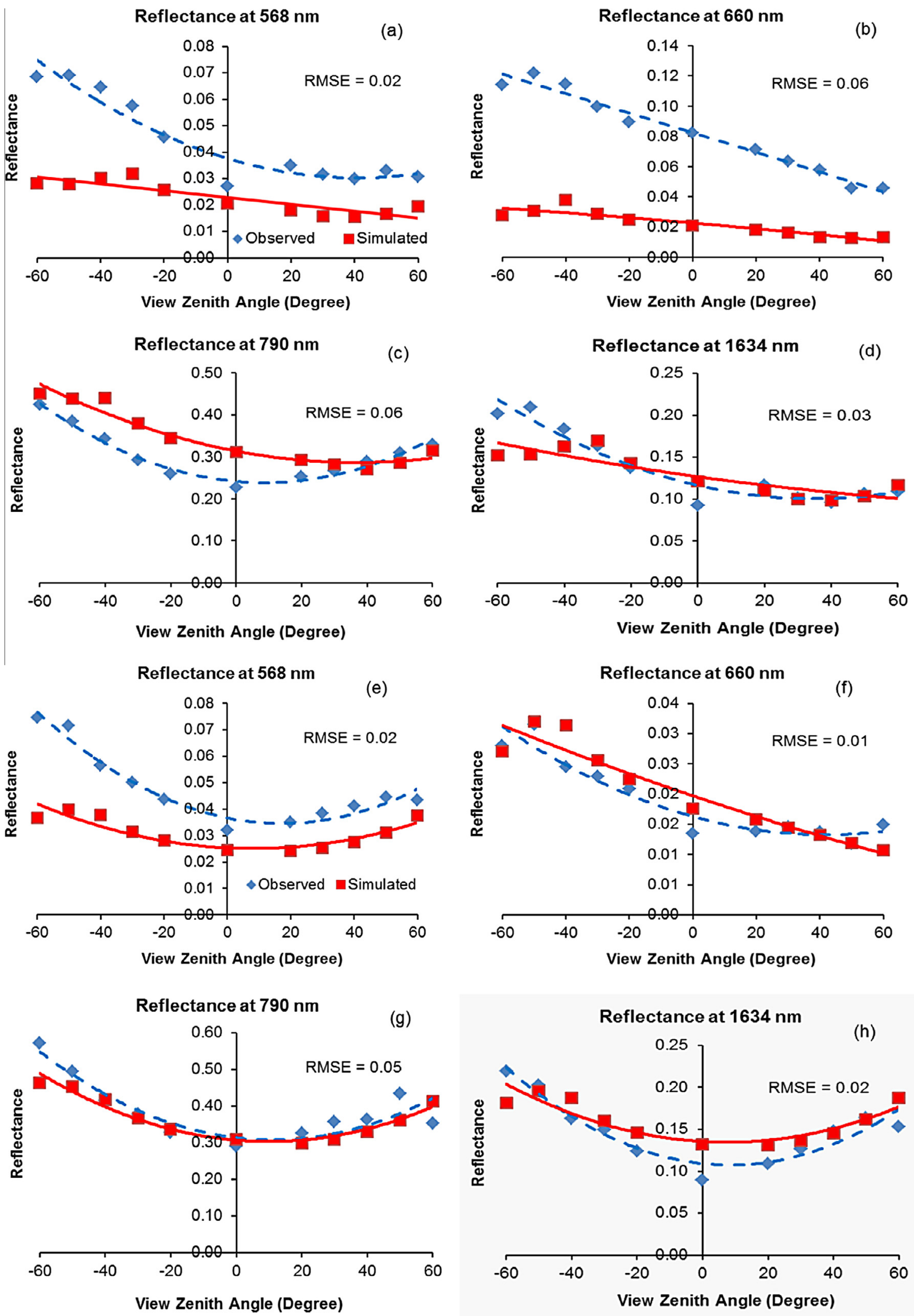

Fig. 1 – Comparison of the observed and model simulated reflectance in the principal plane for N_0 at (a) 568 nm, (b) 660 nm, (c) 790 nm and (d) 1634 nm and for N_{120} at (e) 568 nm, (f) 660 nm, (g) 790 nm and (h) 1634 nm, on 68 DAS.

Table 2 – Comparison of different model inversion techniques for retrieval of wheat biophysical parameters. The values in bracket are probability values of correlation coefficient (*r*).

No. of solutions	C_{ab} ($\mu g\ cm^{-2}$)			LAI ($m^2\ m^{-2}$)			C_w (cm)			CCC ($g\ m^{-2}$)		
	r	RMSE	nRMSE	R	RMSE	nRMSE	*r*	RMSE	nRMSE	*r*	RMSE	nRMSE
Best fit (LUT-I)	0.78 (0.008)	18.3	0.42	0.90 (0.0003)	0.56	0.31	0.17 (0.639)	0.009	0.37	0.89 (0.0004)	0.49	0.60
Best 100	0.83 (0.039)	18.7	0.43	0.94 (0.005)	0.50	0.29	0.16 (0.752)	0.008	0.30	0.93 (0.006)	0.50	0.62
Best 500	0.84 (0.036)	17.0	0.39	0.94 (0.005)	0.49	0.29	0.16 (0.756)	0.007	0.25	0.93 (0.008)	0.48	0.59
Best 1000	0.85 (0.034)	15.6	0.35	0.95 (0.004)	0.48	0.28	0.19 (0.717)	0.006	0.22	0.92 (0.008)	0.46	0.57
Best 10% (LUT-II)	0.71 (0.021)	9.06	0.20	0.90 (0.0004)	0.47	0.27	0.3 (0.393)	0.005	0.19	0.89 (0.0006)	0.35	0.42
ANN	0.87 (0.0009)	23.27	0.55	0.94 (0.0004)	0.52	0.29	0.74 (0.0.012)	0.005	0.19	0.92 (0.0001)	0.54	0.66

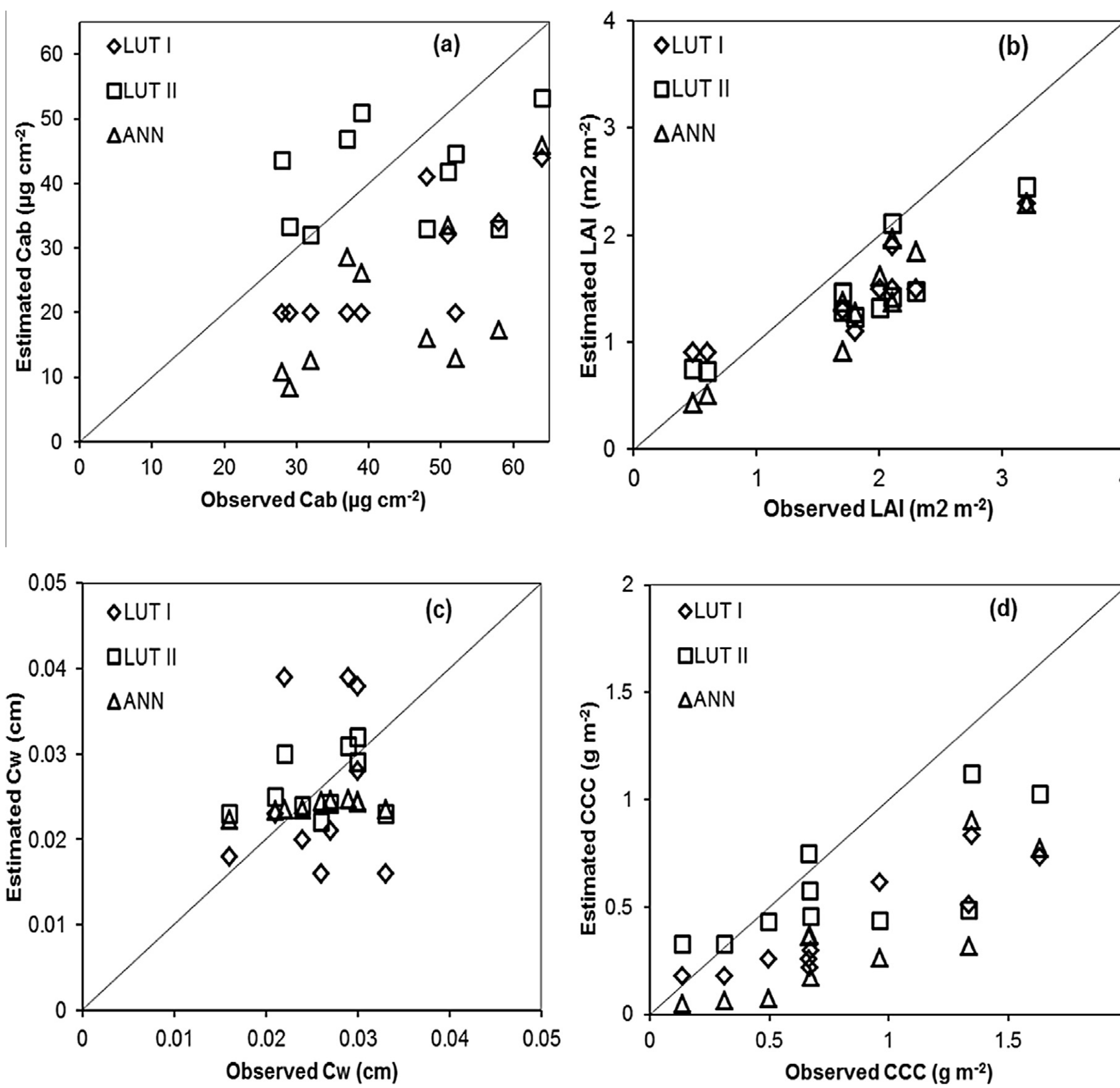

Fig. 2 – Comparison of estimated and observed biophysical parameters of (a) C_{ab}, (b) LAI, (c) C_w and (d) CCC, by three inversion approaches using LISS-3 broadband reflectance.

the best technique of retrieval. To solve these problems of explaining the different characteristics of the data, scientists have discovered a new way of explanation i.e. summary diagram which uses the relationship between some widely known statistical quantities to make compact diagrams that summarize multiple aspects of model performance.

Here we have used the Target diagram [45]. It provides summary information about the pattern statistics as well as the bias thus yielding a broader overview of their respective contributions to the total RMSD (root-mean-square difference). In a Target diagram, the centered RMSD is used as the *X*-axis and the bias as the *Y*-axis over a simple Cartesian coordinate system. The distance between the origin and the model versus observation statistics is equal to the total RMSD. The target diagram (Fig. 3) showed that for C_{ab}, LUT-II gave the best estimates followed by LUT-I and then ANN. The normalized total RMSD was less than 1 for LUT-II. The LAI also showed similar accuracy for LUT-II, LUT-I and ANN with normalized total RMSD being less than 1 in all the cases. CCC was retrieved best by the LUT-II, followed by LUT-I but ANN retrievals showed both large bias and large normalized total RMSD. In case of C_w also LUT-II gave the best retrieval. In case of ANN and LUT-I, the C_w retrievals were poor due to higher bias and higher normalized total RMSD, respectively.

In all the inversion approaches, the general order of estimation accuracy was LAI > C_{ab} > CCC > C_w. LAI estimation accuracy was comparatively better as indicated by significantly high *r*, lower nRMSE values and visual interpretation of target diagram. It was followed closely by C_{ab} which was having similar *r* values but higher nRMSE than LAI estimation. The accuracy of canopy chlorophyll (CCC) estimation was still lower than that of leaf C_{ab}. All the three approaches failed to retrieve C_w as indicated by non-significant *r* values though nRMSE was lowest among the three parameters. These results are in conformity with results of Vohland et al. [50]. They also reported that LAI and C_{ab} were retrieved with useful accuracies in comparison to other biophysical variables. The higher accuracy of LAI estimation by all approaches may be due to the fact that structural variables (e.g. LAI, LAD) determine the total canopy reflectance of crops much more significantly than biochemical variables [6]. The high sensitivity of RED and NIR bands and moderate sensitivity of GREEN band to changes in LAI [39] may have resulted in better simulating the reflectance spectra by PROSAIL leading to relatively accurate inversion.

The relationships between measured and estimated leaf chlorophyll C_{ab} were poorer than for LAI in all inversion techniques. This result is in line with results of previous studies [51,1]. It is argued that there is always poor signal propagation from leaf to canopy scale resulting in poor estimation of leaf biochemical parameters by canopy reflectance [52]. Moreover, it is only the VIS band which is sensitive to leaf chlorophyll

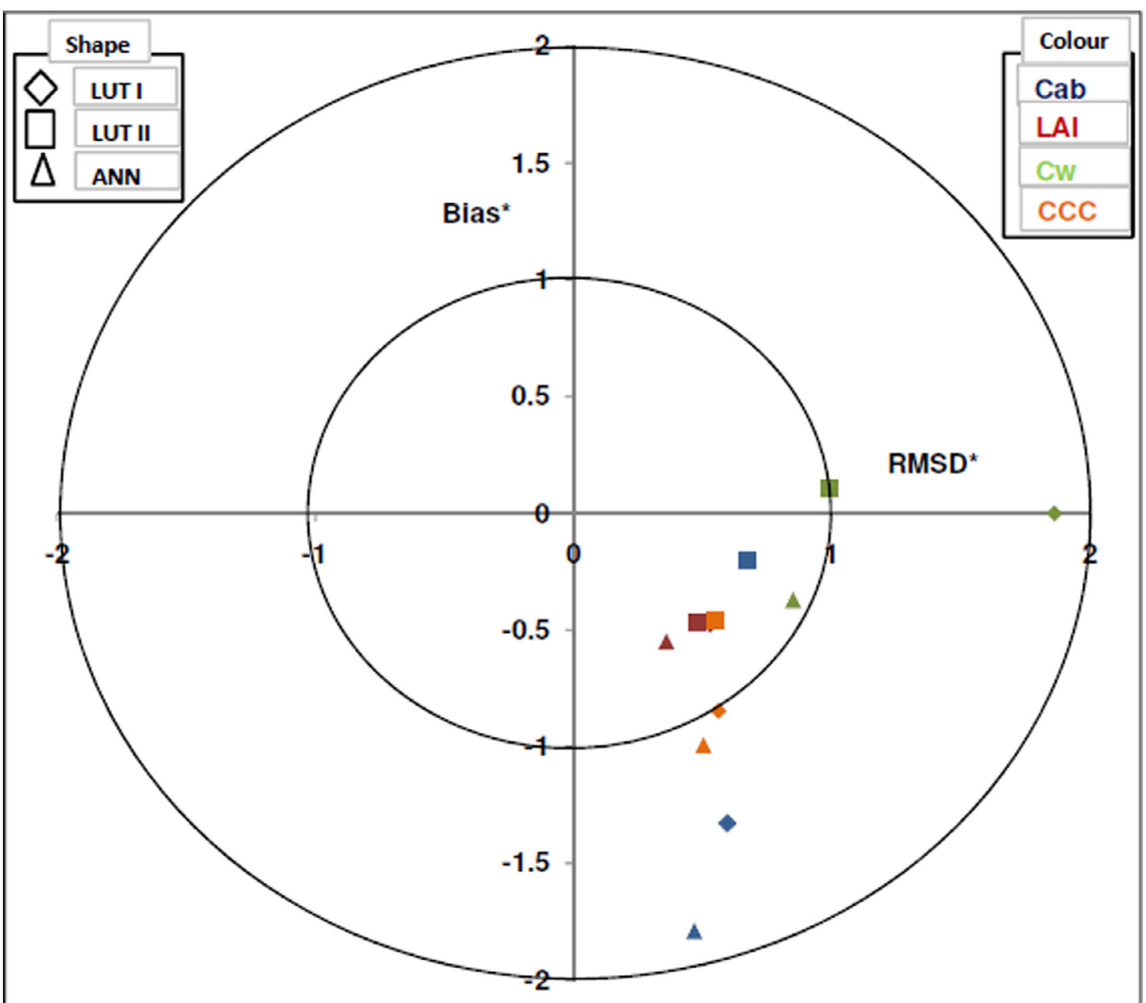

Fig. 3 – Target diagram showing the performance of inversion techniques for all the four biophysical parameters.

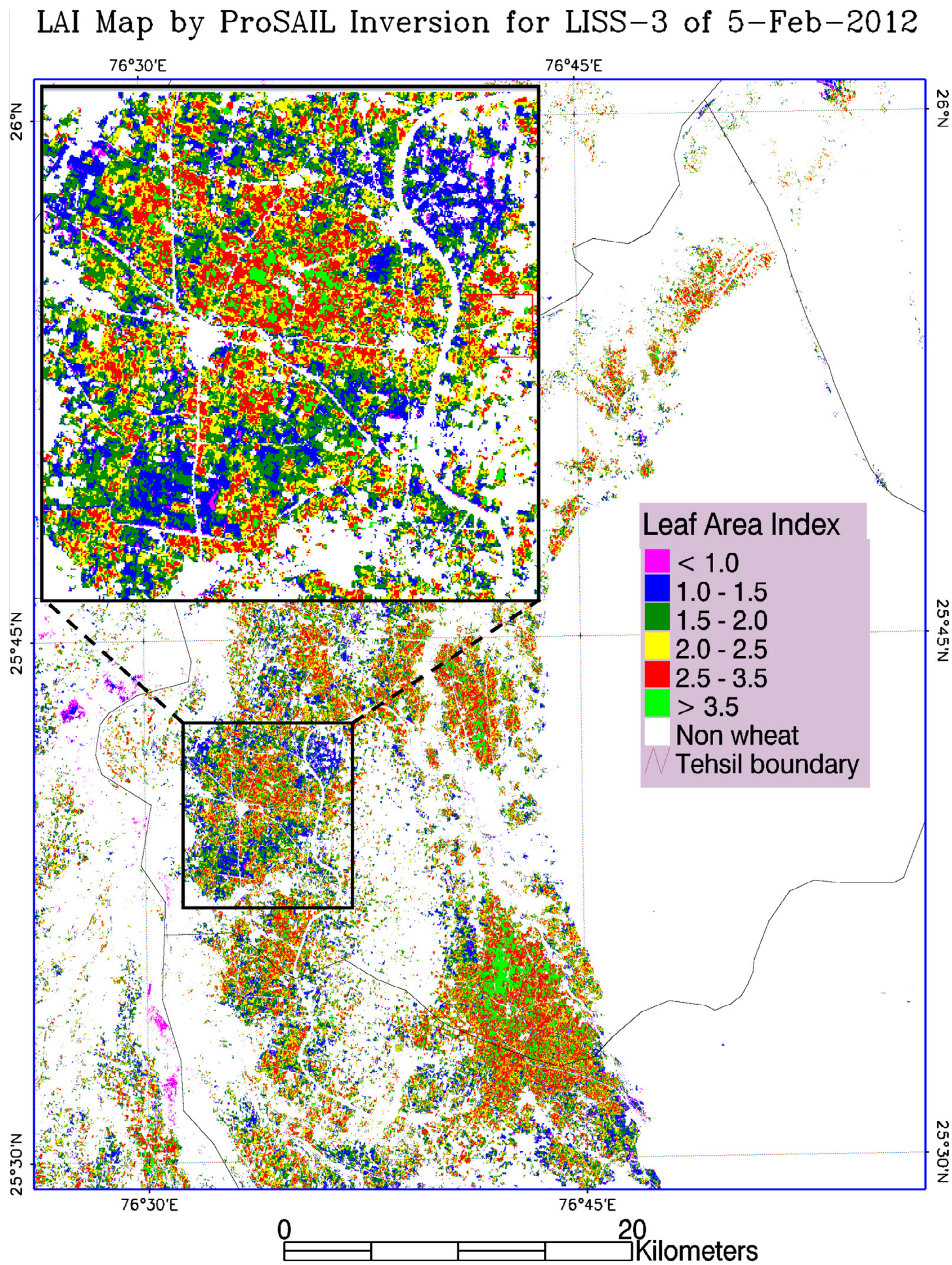

Fig. 4 – LAI map generated through inversion of PROSAIL5B model by LUT-II approach for IRS LISS-3 image of 5-Feb-2012. The inset shows zoomed up LAI image of an area.

variation and this band reflectance has very low dynamic range due to dominance of absorption. So, there is more chance of error in PROSAIL simulation of reflectance in VIS band, leading to poorer estimate of C_{ab}.

A number of studies showed increased robustness and accuracy when estimates of biochemical variables were integrated at the canopy level (e.g. canopy chlorophyll, $C_{ab} \times$ LAI) rather than at the leaf level [21,50]. It means that leaf scales results for chlorophyll are generally inferior to those at canopy level. We have found contradictory results as accuracy of CCC was poorer to that of C_{ab}, mainly on account of higher bias (i.e. nRMSE). The r values of CCC estimation were higher than that of C_{ab} in this study also. The higher nRMSE of CCC in our case may be because both C_{ab} and LAI were generally underestimated.

In the case of leaf water content (C_w), all the three inversion approaches failed as indicated by non-significant r values. On the other hand, the nRMSE in all three inversion approaches was comparatively low. The poor values of r and low nRMSE may be because of narrow range of variation in observed C_w value as our experimental treatments varied only in nitrogen content. As all the three approaches estimated near average value of C_w in all cases, it led to low nRMSE. The study of Jacquemoud and Baret [51] supports our results though accurate retrievals are also reported by others [34].

When comparing performance of inversion approaches, the LUT-II with best 10% solutions outperformed the other two i.e. LUT-I and ANN, in estimating all the three parameters. The study clearly show that in case of LUT inversion, the accuracy of parameter retrieval keep on increasing (lowering of nRMSE) with the inclusion of more number of lowest sorted rMSE solutions. It was seen that for LAI, C_{ab}, CCC and C_w there was significant decrease in error which may be due to the fact that the model was underestimating in some wavebands but when we took best 10% solutions then there was improvement in the estimated results as compared to the observed ones. The inclusion of best 10% of LUT cases produced the most accurate result in this study. Darvishzadeh et al. [1] reported marginal improvement in accuracy when they considered first 100 solutions though statistically non-significant. Some other studies have also considered best 20% of sorted RMSE values as possible solution [22,50].

The ANN approach under performed as compared to LUT even though ANN training time was considerably large and processing computation intensive. The ANN showed severe underestimation in all the parameters. These results are in conformity with the results reported by Vohland et al. [50]. They also found that ANN performance was poor as compared to numerical optimization and LUT. Their study also reported underestimation of all canopy variables by ANN. This may be due to the specific nature of model inversion. While LUT is a radiometric driven approach which seeks for the best reflectance correspondence, the ANN minimizes MSE over the biophysical parameters [15]. ANN also suffered from another drawback that for new training set it produces a different result while LUT is consistent in its result.

As the LAI was retrieved with the highest accuracy and LUT-II proved to be the best inversion technique, the study was extended to the regional scale retrieval of LAI by LUT-II method from IRS-P6 LISS-3 satellite data. The Fig. 4 shows the retrieved LAI map of wheat pixels in Sheopur district of Madhya Pradesh on 5-Feb-2012. The LAI ranged between 0.55 and 4.5 with majority of the pixels having value around 2.0. The Fig. 5 shows the comparison of the retrieved LAI with observed values for selected fields. The results show that the retrieved LAI was underestimated in all the cases with a RMSE of 0.56 which is similar to that obtained in field scale retrievals. The regression line fitted between retrieved and observed LAI was nearly parallel to 1:1 line with highly significant R^2 of 0.87 ($p = 0.01$). These results indicate highly successful retrieval LAI by LUT-II approach from LISS-3 braodband reflectances and the errors were mainly due to the model simulation.

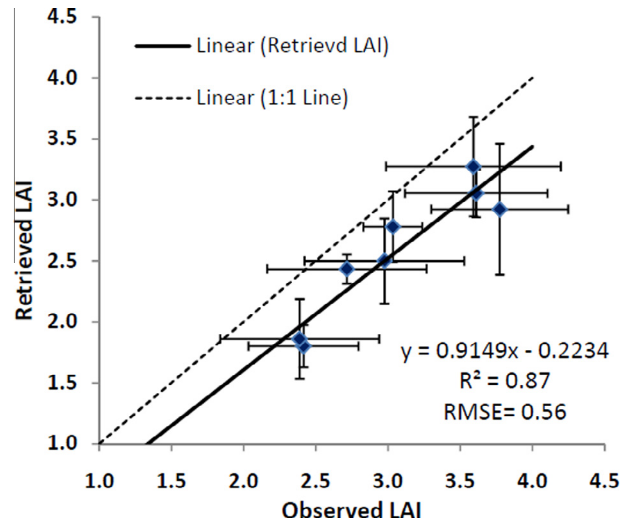

Fig. 5 – Comparison of observed and retrieved LAI of wheat for few sites in Sheopur district.

4. Conclusions

This study evaluated the performance of PROSAIL5B model with field observations for wheat and followed it up with model inversion to estimate wheat biophysical parameters at field scale and regional scale. Among the three inversion approaches, LUT-II outperformed other two approaches indicating that a set of best solutions is a better strategy than using only one best solution. On the other hand, change in results of ANN inversion with each new training set is a major lacuna of this approach and may be avoided.

All the inversion approaches were consistent in the order of accuracy of estimation of biophysical parameters, with order being LAI > C_{ab} > CCC > C_w. So, the deficiencies in the PROSAIL5B model in simulating the crop reflectance have greater influence than the uncertainty in the inversion approaches. There is a strong case for improving the structure of PROSAIL5B model for better simulation of VIS region reflectance for improving the accuracy of C_{ab} retrievals. Further, background soil may be treated as an anisotropic reflector in the model instead of Lambertian reflector to overcome the underestimations in the retrievals, especially for sparse canopy. Though in our study, the C_w was retrieved with lowest accuracy due its narrow range of variation in the dataset, it is expected that its retrieval accuracies may be better for canopies where a larger range of variations occurs.

The retrieval of LAI from satellite data also showed similar errors as that of field data inversion. The study shows that absolute errors in retrievals may be low to moderate though the relative error in the biophysical parameters may be high. But it should be considered in the light of the fact that only four broadband reflectance corresponding to IRS LISS-3 were used for inversion. So, inversion of PROSAIL5B by LUT-II using broadband reflectance is a plausible approach for retrieval of biophysical parameters for a range of applications. The applicability of retrievals may still be high for applications which rely on relative change in parameters, either across space or time. The results of this study shall also help fill the knowledge gaps in generating operational biophysical products using IRS LISS-3 images by space agencies provided complexities arising due to atmospheric noise could be taken care.

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